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Voice analysis in Parkinson's disease - a systematic literature review

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ABSTRACT

Background and aim: Parkinson's disease is a neurodegenerative disease. It is often diagnosed at an advanced stage, which can influence the control over the illness. Therefore, the possibility of diagnosing Parkinson's disease at an earlier stage, and possibly prognosticate it, could be an advantage. Given this, a literature review that covers current studies in the field is relevant.

Methods: The aim of this study is to present a systematic literature review in which the models used for the diagnosis and prognosis of Parkinson's disease through voice and speech assessment are elucidated. Three databases were consulted to obtain the studies between 2019 and 2023: SienceDirect, IEEE Xplore and ACM Library .

Results: One hundred and six studies were considered eligible, considering the definition of inclusion and exclusion criteria. The vast majority of these studies (94.34%) focus on diagnosing the disease, while the remainder (11.32%) focus on prognosis.

Conclusion: Voice analysis for the diagnosis and prognosis of Parkinson's disease using machine learning techniques can be achieved, with very satisfactory performance results, like is demonstrated in this systematic literature review.

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1. Introduction

Parkinson's disease is a neurodegenerative disease associated with a loss of dopaminergic neurons in the substantia nigra, that mainly affects the patient's motor coordination. [1]. In 2019, it was estimated that 8.5 million people suffered from the disease [2]. It shows a higher prevalence in the male sex and in older age groups, but this does not exclude its existence in the younger age groups [2] or in the female community [3]. The diagnosis is mainly based on clinical methods based on the patient's symptoms [4].

Although there is no complete certainty about the cause of the disease, it can be influenced by genetic factors, exposure to high levels of pollution, consumption of certain substances, among others causes [3].

People who suffer from this disease can show motor and non-motor symptoms [2]. Motor symptoms can include bradykinesia, tremors, involuntary movements, rigidity, loss of balance, painful muscle contractions, and difficulty in locomotion. Non-motor symptoms can include cognitive impairment, mental health disorders, sleep disorders, and sensory disturbances. Patients can also be affected by other problems related to these, such as difficulty with swallowing and chewing, and speech changes [1].

Changes in speech occur in about 89% of cases of Parkinson's disease [5]. These changes are noticeable with the occurrence of monotonous speech, a hesitation when starting to speak or speaking too quickly [1], difficulty in word finding, impaired speech or prolonged speech times [5].

In order to prepare this systematic literature review study, a search and subsequent analysis of existing literature reviews was performed on the subject of assessing the voice of patients with Parkinson's disease using machine learning techniques.

In Moro-Velazquez et al. [6], studies published between 1956 and May 2020 are considered. However, this review only evaluates studies that analyze articulatory and phonatory aspects in the speech of Parkinson's patients and does not look much into the other characteristics of the voice. In Mei *et al.*[7], studies from 2009 to February 2020 are presented, with an emphasis on the data used and machine learning techniques. On the other hand, the authors focus on analyzing Parkinson's disease through different symptoms, not just voice and/or speech. In Ngo *et al.*[8], a literature review study is presented on analyzing vocal characteristics in Parkinson's disease, highlighting the features and classifiers used, the performances obtained, among other relevant information. The selection of studies covers the years 2010 to 2021. In Rana et al. [9], studies on voice assessment in Parkinson's disease from 1996 to 2022 are examined, taking machine learning techniques into account. On the other hand, the type of features used is not emphasized. In Amato et al. [10], the type of features, data, and classifiers used in studies between 2017 and March 2022 are mentioned. However, preprocessing techniques are not highlighted. In Skaramagkas et al. [11] and di Biase et al. [12], elements such as data, machine learning techniques, and features used, among others, are mentioned. However, not only voice evaluation was considered. In van Gelderen et al. [13], only studies in which deep learning classifiers were used, are considered, the remaining classification techniques are not considered.

The main contributions of this literature review are: (1) a discussion of the ways in which the diagnosis and prognosis of Parkinson's disease are addressed through voice assessment; (2) identification of the most commonly used databases; (3) the most frequently used features, as well as the methods for their extraction and selection; and (4) the machine learning techniques used to classify the data obtained from speech.

This review is organized into five sections. In Section 1, an introduction to Parkinson's disease and a brief description of the methods currently applied in the field are presented, as well as the main contributions of this review and its organization. In Section 2, the research method used to obtain the studies presented in the following section and the research questions used to carry out this literature review are described. In Section 3, in addition to the description of the studies, the requirements defined for the inclusion and exclusion of articles are also explained and the results obtained are elucidated. The research questions are discussed in Section 4, and the conclusions are presented in Section 5.

Table 1
Keywords used for multidisciplinary search.

Databases	Keywords
SienceDirect, IEEE Xplore, ACM Library	(parkinson disease) AND (speech OR voice) AND (assessment OR processing)

2. Methods

2.1. Search strategy

To conduct the proposed systematic review of the literature, studies found in this area were selected from multidisciplinary databases, according to defined inclusion and exclusion criteria. Therefore, SienceDirect, IEEE Xplore and ACM Library databases were used.

The search, carried out in December 2023, focused on titles, abstracts, and keywords, covering a time interval of five years (2019–2023). The keywords used for each of the databases mentioned above, are displayed in Table 1.

This systematic literature review was developed based on the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) [14] directives.

2.2. Studies selection

The web application Rayyan [15] was used to filter the articles by title and abstract, and duplicate articles were also eliminated.

For the study selection phase, some criteria were defined for the exclusion and inclusion of the studies under analysis.

Exclusion criteria included:

- Articles not written in english, reviews and chapters;
- Studies that did not diagnose or prognosticate Parkinson's disease;
- Studies that did not include a speech or voice evaluation;
- Studies in which the number of patients with Parkinson's disease was less than 10, or that did not include Parkinson's disease subjects;
- Studies that did not use machine learning tools;
- Articles in which the preprocessing, feature extraction and signal classification techniques are not mentioned or in which not enough information is provided about them.

For the included studies, when extracting information from them, only information relating to voice analysis and Parkinson's disease was considered, even if other pathologies or variables had also been covered in the original study.

After careful analysis of the chosen studies, the information extracted was organized as follows:

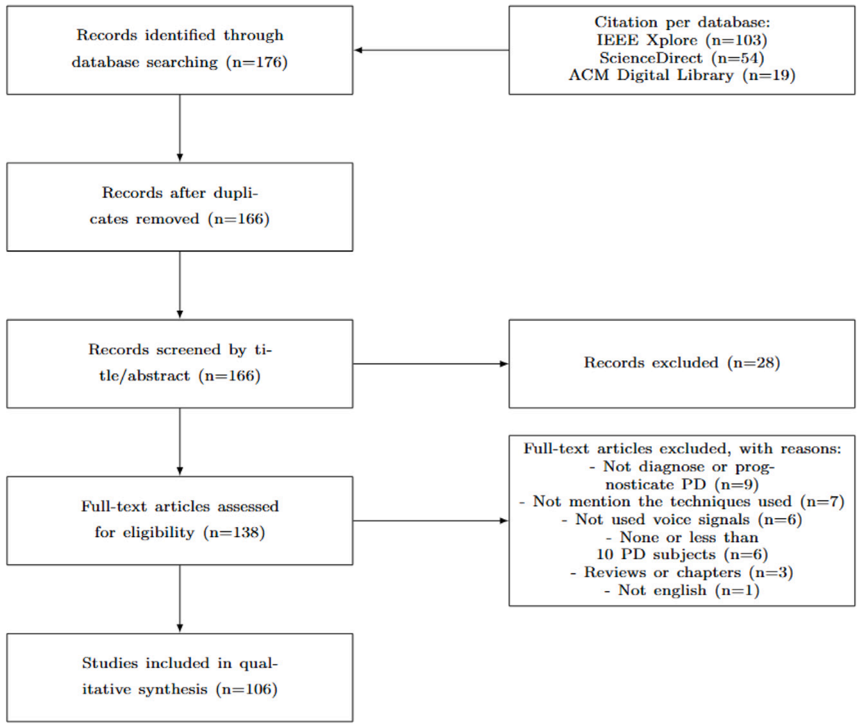

Fig. 1. Flow diagram of the identification and inclusion of studies.

- Study data: such as year and citation;
- Data: the databases used, as well as the number of subjects;
- Algorithm: preprocessing, feature extraction, feature selection and classification methods are outlined;
- Performance: evaluation scores obtained are presented.

2.3. Research questions

To conduct this review, some research questions were established.

- (RQ1) How is the problem of voice and speech assessment in Parkinson's disease addressed?;
- (RQ2) Which features are most used?;
- (RQ3) What are the best classification approaches?;
- (RQ4) What are the main limitations and future possibilities found in the field?.

3. Results

Fig. 1 shows the diagram obtained during the inclusion and exclusion phase of the articles obtained. It also shows the number of excluded articles and the reason for their exclusion.

The study began with a sample of 166 unique entries. After selecting them, taking into account the title and abstract, this number was reduced to 138 articles. Then a more careful selection was made, considering the previously defined exclusion and inclusion criteria, resulting in 32 articles being excluded.

The excluded records are described as follows:

1. Nine studies did not diagnose or prognosticate the disease;
2. Seven studies did not mention the techniques used to process or classify the data or not enough information is provided about them;
3. Six studies did not use voice signals;
4. Six studies have less than ten Parkinson's disease patients or do not include Parkinson's disease subjects;
5. Three articles are reviews or chapters;

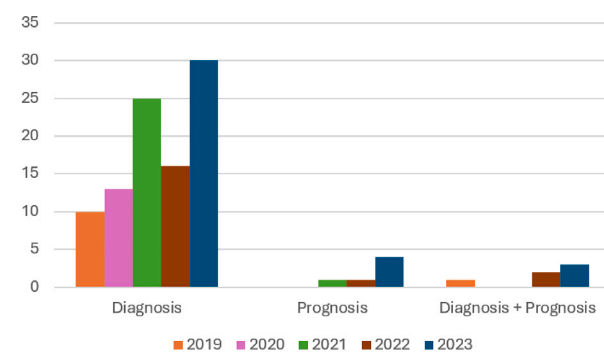

Fig. 2. Publication trend of the included studies, according to year and purpose.

6. One study is not in English;

The final selection comprises 106 articles, which are described in Tables 2 and 3.

The information is organized according to the purpose of the study, i.e. between diagnosis and prognosis. The studies in which both diagnosis and prognosis were performed, even if diagnosis was the main objective, are listed in Table 3.

Fig. 2 shows the number of publications, included in this review, published in each year. Moreover, it distinguishes the papers published in each year that were focused on the diagnosis, prognosis, or both. Through the analysis of the graph, an increase in the number of publications regarding the analysis of voice in Parkinson's disease in recent years can be noted. Moreover, since 2021 some publications have focused on the prognosis of Parkinson's disease, with an increase in publications with this focus in 2023. Regarding publications focused on both diagnosis and prognosis, only one study, with this focus and published before 2022, was included in the review. There was also an increase in the number of studies focused on diagnosis and prognosis in 2023.

Table 2
Related works - Diagnosis.

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[16]	2019	2 databases	20 PD/20 HC + 28 PD		Praat software (database)	$\chi2$ statistical model (noisy features elimination); SSFH (Selection of samples, features and hyper-parameters) approach	NN	LOSO CV	**ACC**:97.5%–100%; **Sen**:100%; **MCC**:0.951; **Spec**:95%;
[17]	2019	UCI	188 PD/64HC	SMOTE (balanced class distribution)	753 features		SMOTE + Random florest	50/50 (training/test) 10-fold CV	**ACC**:94.89%; **F1-score**:0.949; **Kappa value**:0.894; **Prec**:95.1%; **AUC**:0.991; **Sen**:94.9%
[18]	2019	UCI	188 PD/64 HC	Min–max normalization	TQWT; MFCCs; WT; Baseline, Vocal fold; TF features		CNN + SVM	LOPO CV	**ACC**:86.9%; **F1-score**:0.917; **MCC**:0.632 (Model-level combination)
[19]	2019	Collected database	188 PD/64 HC	Standardization	Praat; Voice Analysis Toolbox (Baseline Features; Time frequency features; MFCCs; Vocal fold features; WT; TQWT)	mRMR	SVM (linear+RBF); MLP; NB; LR; RF; k-NN	LOSO CV	**ACC**:86%; **F1-score**:0.84; **MCC**:0.59 (SVM-RBF)
[20]	2019	Neurovoz	52 PD/56 HC	Normalized, framed and parameterized (RASTA-PLP)	RASTA-PLP		Siamese LSTM-based NN	k-fold CV	**EER**:2.9% (sentence 1), 1.9% (all 5 sentences)
[21]	2019	VGFR Dataset (gait); UCI (voice)	100 PD/40 HC (train) + 38 PD/17 HC (test) (voice) (samples)	Normalization (standart) + weight measure (training data) (voice)	Variations of Fundamental Frequency, ratio of noise and tonal components, dynamical complexity measures - Voice Impairment Classifier (voice)		ANN (voice)	Data splitting; Validation of Voice Imp. Class.; Comparison with XG Boost, SVM, MLP	**ACC**:89.15% (Voice IC)
[22]	2019	PC-GITA + SVD	50 PD/50 HC + 2000 samples (pathological speakers (not necessarily PD))	Randomly signal rolling; Random band-pass filter (low/high pass frequencies)	Frequency-based features from spectrograms		Modified ResNet-18 (ReLU)	90/10 (training/validation); 10-fold V	**ACC**;91.7%; **F1-score**:0.92; **Prec**:92%; **AUC**:0.93 **Sen**:92%
[23]	2019	2 databases + UCI	22 PD + 30 HC + 18 PD	Normalization; Linear Regression; Random split (k-fold)	Praat script (19 Features: Jitter; Shimmer; Picth; Harmonicity; Gender); PCA	Feature selection	Naïve–Bayes (NB);Perceptron algorithm; RF; SVM (RBF);NN	LOO CV; Levene and Kruskal tests; k-fold	**ACC**: 99.94% (RF); 92.38% (SVM); 91.10% (NN)
[24]	2019	Hand PD Spiral + Hand PD Meander + Speech PD + Voice PD	23 PD/8 HC (speech) + 20 PD/20 HC (voice)			Modified Grey Wolf Optimization algorithm	MGWO + ML (DT/RF/KNN (K=3))	70/30 (training/test)	**ACC**: 94.83%
[25]	2019	mPower database	993PD/1289HC		OpenSmile software (62 voice parameters);PCA; K-means clustering	ANOVA (5 parameters)	MLP; LR	Data splitting	LR **ACC**:77.3%; **AUC**:0.832;
[26]	2020	UCI	23PD/8HC	Jupyter notebook; Exploratory Data Analysis (EDA)	22 voice features		13 different ML models		RF **ACC**:94.92%; **AUC**:0.9397
[27]	2020	UCI + PC-GITA	25 PD/20 HC + 25 PD/20 HC	Downsampling	Voice analysis toolbox and MIR toolbox - Acoustic feature: (27 features); MFCC; EMD (IMF features:(Energy; Entropy; Spectral entropy; Intrinsic mode functioncepstral coefficient (IMFCC); Statistical features))		SVM; RF	80/20 (training/test); 10-fold CV; LOOCV; LOSO test; Cross-database evaluation	**ACC**: 98% (SVM-IMFCC)/100% (RF-IMFCC); **AUC**: 1.00 (RF)/0.99 (SVM); **Sen**: 100% (SVM); **Spec**: 92% (SVM)
[28]	2020	UCI	23 PD/8 HC	Normalization	Traditional measures: Praat software (short-term autocorrelation); Nonstandard measures: (Time Series Analysis)		ANN (Levenberg–Marquardt training algorithm); KNN	70/25/5 (training/test/validation) (ANN); 70/30 (training/test) (KNN);	**ACC**: 96.7% (ANN), 79.31% (KNN, k=1)
[29]	2020	UCI	23 PD/8 HC (139/56 (training/test) sustained vocal phonations)	Standardization; Zero score and Min–max normalization	Features: Frequency, jitter, shimmer, voice tone (HNR, NHR) Recurrent Period Density Entropy, Pitch Period Entropy		Naïve Bayes; LR; K-NN; RF	Performance metrics	**ACC**: KNN: 90.2% (K=5);**F1-score**: 0.895; **Prec**: LR: 93%; **Sen**: RF: 92.8%
[30]	2020	PC-GITA	50 PD/50 HC	Hamming window; no overlap; NFFT	Alexnet; Handcrafted feature-based model (RMS; spectrum; zero crossing; pitch; entropy; MFCC; statistical features); Spectrograms; Mir toolbox		Transfer learning method (Alexnet); SVM; RF; MLP	5-fold CV	**ACC**: (1) MLP:99.7%/(2) RF:99.1% (Deep features)
[31]	2020	1 dataset (AC+SP)	197 AC/198 SP (HC+PD)	80/20 (training/test); Praat software:	Voice (V) and Unvoiced (UV) parts; Phonation and Speech;	Dimensionality reduction	KNN (K=1); SVM	Performance metrics	**ACC**: AC: 86.52%/SP: 84.14%; **Prec**: AC: 86.52% /SP: 73.78%; **AUC**:AC: 0.8436/SP: 0.7815 (KNN)

(*continued on next page*)

Table 2 (*continued*).

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[32]	2020	Audio database (Medical University of Warsaw)	22 PD/22 HC	Overlapping; Segmentation: Δ and $\Delta\Delta$ parameters	LFCC analysis; MFCC; GTCC		LDA; K-NN (k=2)	11-fold CV; linear cepstral technique (Δ and $\Delta\Delta$)	**ACC**: LDA-MFCC:86.4%/ K-NN-MFCC: 83%; **Sen**: LDA-GFCC: 90.9%/ K-NN-MFCC:91.4%; **Spec**:Δ+$\Delta\Delta$: 90%/ LDA-MFCC:90.9%/ K-NN-MFCC:77.3%
[33]	2020	Hungarian corpus	83 PD/33 HC	Normalization; VAD (Voice Activity Detection); Forward-backward divergence segmentation (FBDS); Transient-stationary segmentation (TSS);	Features: Length of segments, Speech rate and Speech rate changes		C-SVC+RBF	LOSO CV	**ACC**: TSS/FBDS:76%/73%; **F1-score**: TSS/FBDS:0.72/0.69; **Sen**: TSS/FBDS:61%/60%; **Spec**: TSS/FBDS:SYL- 91%/85%
[34]	2020	PC-GITA	50 PD/50 HC		Short Time Fourier Transformation (STFT) - Spectrogram; Continuous Wavelet Transformation (CWT) - Scalogram; Time-frequency features		Stacked auto-encoder DNN with a Softmax classifier; SVM	80/20; hold-out validation	(Softmax) **ACC**: STFT: 87%/CWT: 82%
[35]	2020	UCI	23 PD/8 HC		22 phonetic features	Univariate Selection, Recuesive feature elimination, Feature importance	Classification and Regression Trees (CART); SVM; ANN	Performance metrics	**ACC**: (before FS/after FS) CART: 85.23%/90.76%/ SVM: 79.98%/93.84%/ ANN: 80.25%/91.54%
[36]	2020	Spiral dataset + UCI Voice dataset	20PD/20HC	K- means clustering			DT	Data splitting	**ACC**:95%
[37]	2020	Albayzin + VoxCeleb + Neurovoz	43PD/46HC	Normalization, filter, Re-sample; VAD	x-Vectors (MFCC)+ i-Vectors (PLP); PCA		Probabilistic Linear Discriminant Analysis (PLDA)	Data splitting; 10-fold CV	x-Vector (16 kHz) **ACC**:90%, **AUC**:0.94, **Sen**:91%, **Spec**:89%
[38]	2020	1 PD dataset	60PD/60HC	Segmentation	CNN-LSTM; 36-dim MFCC		CNN-LSTM	5-fold CV	**ACC**:90.98%
[39]	2021	UCI	188PD/64HC	Rescaling; min–max normalization	Autoencoder (Baseline Features; Time Frequency Features; MFCCs; Vocal Fold Features; TQWT		SVM; XGBoost; MLP; LR	5-fold CV	Logistic Regression + voting **ACC**: 97.22%
[40]	2021	(1) MMPD + two noise data sets: (2) 4 types of noise; (3) 3 types of noise (a subset of NOISEX-92)	(1) 400 PD/400 HC/8000 random samples/20 outlier samples	Segmentation; Noise reduction, Dereverberation, Declipping algorithms	13 PLP coefficients; 12 MFCCs; noise; reverberation; nonlinear distortion		Gaussian mixture models (GMMs)	5-fold CV; 10-fold CV	**AUC**:0.95 (Clean signals)
[41]	2021	Collected dataset	33 PD/18 HC	Auto-cutting algorithm (BP filter; Down Sampling; Segmentation; TKEO Operator; Sum; Smoothing; Compressor; Amp Treshold; Time Treshold); Normalization	Standard Measures (Normalized Correlation Function, HNR (Autocorrelation Function)); Nonstandard Measures (RPDE; DFA); Cepstral Measures (CPPS; MFCC)		SVM (SMO; Matlab SVM);ANN (MLP); KNN (RSL, IBk)	75/25; 10-fold CV	**ACC**:97.3%/95.4%/ 87.6%/79%/91.2%; **F1-score**:0.97/ 0.94/ 0.84/ 0.68/ 0.90; **AUC**:0.97/ 0.94/ 0.91/ 0.74/ 0.95 (RSL/Ibk/MLP/SMO/Matlab SVM)
[42]	2021	(1) LSVT voice rehabilitation dataset + (2) UCI	14 PD + 20 PD/20 HC		Autoencoder	L1 regularization feature selection methods	New deep dual-side learning ensemble model	LOSO CV	**ACC**: (1) 98.49%/ (2) 99.67%; **Sen**: (1) 98.4%/ (2) 99.35%; **Spec**: (1) 99.1%/ (2) 99.7%
[43]	2021	(1) NewHandPD (handwriting) + (2) PC-GITA (voice)	50 PD/50 HC (voice)	(2) Resampled to 16kHz; Converted to a Mel fbank spectrogram using a 25 ms Hamming window every 10 ms	Spectrogram		(2) Audio Spectrogram Transformer Algorithm	80/20 (training/validation); 5-fold CV	**ACC**:(2) 87.5%
[44]	2021	MDVR-KCL	16 PD/21 HC	Parselmouth library (Python)	Praat; 12 features (Jitter class; Shimmer class; HNR)		Decision Tree; Resnet50-NN model	Performance metrics (Confusion Matrix) (1000 iterations)	**ACC**: DT:61.2%/ RN50:97.3% **AUC**: DT:0.5278/ RN50:0.7232
[45]	2021	UCI	23 PD/8 HC		Correlation Heat map (relationship between features)	Feature Selection	KNN; SVM; RF; NB; LR; Meta Classifier Model; Bagging Model; DT; Adaboost; Gradient boosting	Performance metrics (Confusion Matrix)	(best) **ACC**: KNN: 94.92%; **F1-score**: MCM:0.9655; **AUC**: KNN:0.9455; **Sen**: SVM/GB/DT/BM:100%
[46]	2021	1 Voice database	188 PD/64 HC	Normalization (min–max); Data cleaning; SMOTE			(Stacking classifier and Voting classifier technique) AdaBoost; Extra Trees classifier; DT	80/20 (train/validation); 10-fold CV	**ACC**: Stacking classifier:92.2%/ Voting classifier: 83.57%
[47]	2021	UCI (1) Acoustic dataset + (2) Parkinson's dataset	23 PD/8 HC + 40 PD/40 HC		Acoustic features - (1) 22 features; (2) Pitch and Amplitude local perturbation measures, noise features, Spectral envelope and nonlinear measures		CNN (ReLU); ANN (Levenberg–Marquardt (LM))	85/15 (train/validation); Confusion matrix	**ACC**:((1)/(2)) ANN: 82.76%/72.22% CNN: 93.10%/88.89%
[48]	2021	Collected Dataset "De Novo PD and Healthy subject's data"	51 PD/51 HC		6373 Acoustic Statistical Parameters (Spectral, Prosodic, Voice quality and Cepstral)	Filter (forward greedy step-wise filter + CFS evaluator); Ranker (Correlation, Information Gain, and Gain Ratio)	Naive-Bayes; SVM-SMO; MLP	10-fold CV; Statistical Validation (Iman and Davenport test, Wilcoxon's test, Nemenyi's test)	**ACC**: NB:94.34%/ SVM-SMO:93.806%

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Table 2 (*continued*).

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[49]	2021	GYENNO SCIENCE Parkinson Disease Research Center	30 PD/15 HC	Librosa	NeuroSpeech software (phonation (P); articulation features (A)); DL Models: linear (STFT) spectrogram; Mel-scaled STFT spectrogram; Constant-Q transform spectrogram; PCA		ML models (DT, MLP, KNN, Gaussian Naive Bayes, SVM); DL models (CNN, RNN); Bidirectional LSTMs model	(1) 10-fold CV; (2) training/testing sets	(best) RNN (B.LSTM) **ACC**: (1) 84.29%; **F1-score**: (1) 0.8852; **MCC**: (1) 0.6603; **Sen**:(1) 87.34%; **Spec**: (1) 91.11%
[50]	2021	2 voice datasets	18 PD/20 HC + 20 PD/20 HC	Normalization	238 features - Praat software (Time/frequency domaine: Jitter, Shimmer, HNR, Pitch); Voice Analysis Toolbox (Wavelet Transform, RPDE, DFA, PPE); Cepstral domaine: MFCC, PLP, RASTA-PLP	RELIEF algorithm	SVM (RBF and Polynomial); KNN	train/validation; Performance metrics; k-fold CV (k=5)	(SVM'poly') **ACC**: CD:80%; **Sen**:CD:69%; **Spec**: CD:100%
[51]	2021	PC-GITA + Parkinson's foundation of Medellín	50 PD/50 HC + 20 PD/20 HC	Downsampling	STFT; Non-negative matrix factorization; TF-based feature (Renyi entropy; 17 features); Baseline/Acoustic features (jitter, shimmer, GNE, VFER, HNR, NHR, GQ); MFCC		SVM (classification); SVR	Kruskal–Wallis tests; LOSO-CV (train); 80/20 (train/test)	TF features: vowel /e/ - **ACC**:92%; **F1-score**:0.92; **MCC**:0.84; **AUC**:0.99; word /petaka/ - **ACC**:97%; **F1-score**:0.98; **MCC**:0.96; **AUC**:0.97
[52]	2021	MDVR-KCL + Collected Dataset	16 PD/21 HC + 20 HC	Segmentation; Noise reduction; Re-sampling (Audacity software)	RSSD signal decomposition technique; TQWT technique; SALSA; Time-Frequency analysis; PSD calculated (converted into a signal image)		CNN model	(1) 70/30 (training/validation); (2) 50/25/25 (training/validation/ testing); Kolgomorov-Smirnov test	**ACC**:98.12% (1)/87.50% (2); **F1-score**: 0.97 (1)/ 0.76 (2); **Prec**: 96% (1)/ 100% (2); **AUC**: 0.88 (2); **Sen**: 97% (1)/ 62% (2)
[53]	2021	mPower app	18660 HC/8442 PD (train); 4628 HC/2147 PD (validation); 200 HC/200 HC (test) - voice recordings	Downsampling and reshaping	DCT spectrogram		CNN models (DenseNet-161, ResNet-50, SqueezeNet1-1)	Performance metrics	DN-161 - **ACC**:89.75%; **Sen**:91.50%; **Prec**:88.40%
[54]	2021	Mobile PD Study	700 PD/700 HC - audio	Normalization	70 features - Shimmer, jitter, Min + max pitch, min. tone, HNR, n° pulses, fundamental frequency, MFCCs, Dimensionality reduction technique: HCF	PCA	SVM; RF; LR; MLP	Assessment metrics (confusion matrix)	SVM **ACC**:88%; **AUC**:0.919
[55]	2021	3 datasets	195 rows	Praat	22 characteristics	Feature selection	Extra Tree, LR. KNN, RF, SVM, DT	Data Splitting	KNN **ACC**:97.44%, **Prec**:100%, **Spec**:100%, **Sen**:96.55%, **F1-score**:0.9824
[56]	2021	PC-GITA	50 PD/50 HC	Frame process (25 ms); Hamming window and 50% overbinning; VMD method;	Mel-Spectrogram extraction		ResNet-LSTM network (Softmax)	10-fold CV	ResNet101-LSTM (with VMD) (best) **ACC**: 98.61%; **Prec**: 96.11%; **Sen**: 95.93%
[57]	2021	1 Dataset	20 PD/14 HC	Pre-emphasizing, framing, windowing	Discrete wavelet transform; Formant frequencies (LPC); Time-domain energy and ZCR; MFCC; Shannon entropy decompositional features	Genetic Algorithm	SVM	train/test; 10-fold CV	**ACC**:DWT+MFCC+SVM: 91.18%/ DWT+MFCC: 86.84%
[58]	2021	PC-GITA	50 PD/50 HC	Speech: downsampled; Features: normalization mean, standard deviation, min, max, kurtosis, skewness (Baseline features), downgrading, WLP analysis (Glottal features)	Traditional pipeline approach (Baseline features (Articulation, Phonation, Prosody) (NeuroSpeech toolkit) + glottal features (IAIF and QCP analysis) (APARAT Toolbox)); End-to-end architecture (raw time-domain waveform (speech signal, voice source (ZFF)) + glottal features)		SVM (TPA); CNN+MLP (EEA)	10-fold CV; 90/10 (train/test) Train:90/10 (train/validation)	TPA/EEA (best) **ACC**: B+G(QCP): 67.93%/ G(QCP): 68.56%; **Sen**: B+G(QCP): 69.71%/ G(QCP): 63.4%; **Spec**: G(QCP): 70.43%/ Voice(ZFF): 78.86%
[59]	2021	UCI	23 PD/8 HC	Normalization	Original DB: 22 features; Filtered DB: 14 features (Original processed to obtain a new filtered database)	Multi-agent Feature Filter (MAFT) Algorithm (Feature selection and evaluation)	Hybrid Model (binary CNN + 3 feature selection algorithms (GA, AO, and M-BGD))	10-fold CV (100 tests); 90/10 (train/test); Standard evaluation metrics	(Original/Filtered DB) **ACC**:93.7%/96.9%; **F1-score**:0.922/0.943: **Prec**: 92.4%/93.4%; **AUC**: 0.91/0.93; **Sen**: 91.5%/92.2%
[60]	2021	UCI	188 PD/64 HC (564 PD + 192 HC rows)		7 compressed feature vectors	Adaptive Crow Search Algorithm (ACSA)/CROWD autoencoder	SVM; LDA; GBM; RF; NB; LR	10-fold CV; Standard metrics	(N° features:7) LDA - **ACC**: 96.4%; **Sen**:97.1%; **Spec**: 98.5%

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Table 2 (*continued*).

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[61]	2021	Hand PD meander and spiral (1) + PD speech (2) + PD acoustic (3) - UCI + Parkinson Disease Classification Data Set (speech 2) (4)	(2) 20 HC/20 PD (26 samples)/28PD + (3) 40 HC/40 PD + (4) 64 HC + 188 PD	Normalization		Multi-filter hybrid feature selection algorithm model based on discrete artificial bee colony (MFABC)	KNN, RF, SVM, AdaBoosting, DT, Bayes and discriminant analysis classifier (DAC)	Split into train/test (70/30);	Multiple classifiers - **ACC**: Speech: 100%/ Acoustic: 100%/ Speech 2: 94.05%
[62]	2021	UCI	24PD/8HC	Standard Scaler class method	22 features	Sequential Backward Selection (SBS) method	Proposed ensemble approach (18 ML/Deep classifiers)	LOO	(MLP, DT, KNN, NB, SGD, LD)**ACC**:90.6%
[63]	2021	1 dataset	23PD/8HC		PCA; 24 features	Correlation of the features	SVM	Data splitting	**ACC**:79.3%, **Sen**:85.7%, **Prec**:85.7%, **F1-score**:0.857, **AUC**:0.891
[64]	2022	UCI	23 PD/8 HC	Standardization; train/test; Features scaling	22 extracted features; PCA		SVM; RF; KNN	Performance measurements	RF (best) **ACC**:95%; **Prec**:96.9%; **Sen**:96.9%; **F1-score**:0.969; **AUC**:0.977
[65]	2022	CLP data + PC-GITA	135 CLP/58 HC + 50 PD/50 HC	Data augmentation method; SpecAugment data augmentation	Spectrogram (126-time steps and 128 Mel-scale frequency bins)		IPWOA-DCNNs	10-fold CV; 80/10/10 (train/validation/ test)	**ACC**:95.77%; **F1-score**:0.9544; **Prec**:96.33%; **Sen**:93.33%; **Spec**:93.55%
[66]	2022	(1) GYENNO SCIENCE database (collected)+ (2) PC-GITA	30 PD/15 HC + 50 PD/50 HC	Overlapping; batch normalization; dimensionality reduction; log Mel-spectrograms	Time series dynamic features - Articulation features (NeuroSpeech); Phonation features (NeuroSpeech); Subset of Surfboard components		2D-CNN + 1D-CNN	(1) 60/40 (2) 80/20 (train(validation) /test)	(1) vowel /a/; (2) simple/complex sentences - **ACC**:(1) 81.6%/ (2) 92%; **F1-score**:(1) 0.8766/ (2) 0.9104; **MCC**:(1) 0.5847/(2) 0.856; **Sen**:(1) 79.17%/ (2) 91.21%; **Spec**:(1) 98.33%/ (2) 100%
[67]	2022	PC-GITA	50 PD/50 HC	Data augmentation; Re-scale	STFT (log-frequency power spectrograms); Articulatory and Phonatory aspects		CNN (optimization) (SGD optimizer algorithm)	10-fold CV	(best) vowel /a//words(10) - **ACC**:92.33%/85%; **Spec**:98%/86.2%; **Sen**:86.67%/83.8%; **AUC**:0.9438/0.9145
[68]	2022	PC-GITA + SVD (training) + Vowels dataset (training)	50 PD/50 HC + 1355 D/687 HC	Data augmentation; Gaussian blurring; log-frequency spectrograms resize	STFT (spectrogram); CNN (hidden layers)		MFT CNN (ResNet50 and Xception architectures)	90/10 (train/test); 10-fold CV	**ACC**:99%; **AUC**: 0.896; **Sen**: 86.2%; **Spec**:93.3%
[69]	2022	CLP data + PC-GITA	135 CLP/58 HC + 50 PD/50 HC	Data augmentation; SpecAugment data augmentation	Spectrogram (126-time steps and 128 Mel-scale frequency bins); STFT		IPChOA-DCNN model	10-fold CV; 80/10/10 (train/development/ test)	**ACC**:96.22%; **F1-score**:0.9623; **Prec**:97.01%; **Sen**:94.18%; **Spec**:94.25%
[70]	2022	PC-GITA	50 PD/50 HC		Hamming window; 13 coefficients of MFCCs and SFFCCs; SDC features		LSTM and BiLSTM models (LSTM; BiLSTM; MHA-BiLSTM)	Performance measurements; 5-fold CV	(LSTM/BiLSTM/MHA-BiLSTM) **ACC**:MFCCs+SDC: 77.71%/81.5%/85.02%; **F1-score**: SFFCCs+SDC: 0.807/0.832/0.827
[71]	2022	Kaggle/UCI	195 recordings	Min-Max Scaler (Normalization)	22 features		LightGBM	Performance measurements; data splitting	**ACC**:97.56%; **F1-score**:0.985
[72]	2022	UCI	23 PD/8 HC		22 features		LR; KNN; SVM; RF; Adaptive Boosting; Stacking	Performance measurements; Data splitting	Stacking (best) **ACC**:93%; **F1-score**: 0.94; **Prec**: 94%
[73]	2022	iPrognosis app (Gdata (4 languages)/Sdata (3 languages))	106 PD/392 HC (train) + 39 PD/24 HC (test)	Standardization; Resampling; Digital zero removal; Direct Current (DC) offset removal; Normalization	Auto-correlation combined with peak pruning (pitch); discrete cosine transform (13 MFCCs, 22 BBE)	Lasso, Ridge, Gini Impurity and ANOVA-based selection	LSVM, LR, RF, Multiple Instance Learning (MIL)	LOSO CV (GData)	**AUC**: 0.69/0.68/ 0.63/0.83 (English/Greek/German/ Portuguese-speaking)
[74]	2022	UCI	23 PD/8 HC (195 recordings (147 PD + 48 HC))		22 characteristic attributes for dysphonia		Optimal XGBoost (randomized search and grid search)	Data splitting; Cross-validation	**ACC**:96%; **F1-score**:0.97; **Prec**:100%; **AUC**:0.97; **Sen**:95%
[75]	2022	UCI	188 PD	Standardization	Vocal fold, TQWT Features, Wavelet Features, MFCC, baseline features	Mapping feature importance (XGboost feature significant)	XGBoost	Data splitting; Performance measurements (Confusion matrix)	**ACC**: All Features:84.80%/ (1) excluded (ddaShimmer,locShimmer) 85.60%/ (2) excluded (locDbShimmer, meanNoiseToHarmHarmoniciy,ppq5jitter, apq5Shimmer, ddpJitter, rapJitter,PPE): 84.40%
[76]	2022	UCI	23 PD/8 HC (195 recordings)	Data cleaning; Missing values handling; Categorical Variables transformation; Oversampling (SMOTE)	24 clinical features		LightGBM; RF; XGBoost, AdaBoost, Bagging, DT, LR, SVM, KNN, NB	80/20 (train/test); hold-out validation technique	(LightGBM) **ACC**:95%; **F1-score**:0.90; **AUC**:0.96; **Sen**:100%; **Spec**:93.33%
[77]	2022	UCI	40 PD/40 HC	Heatmap	44 acoustic features		FFNN	Cross-entropy; Confusion matrix; Data splitting	**ACC**:85%; **F1-score**:0.8435; **MCC**:0.7024; **Prec**:80.83%; **Sen**:88.18%; **Spec**:82.31%
[78]	2022	UCI	23 PD/8 HC (195 recordings)	Data cleansing; Heat map; Normalization; Feature Scaling (MinMax scaler method)	Dense and activation layers		DNN Model (5 layers)	70/30 (train/test)	**ACC**: 94.87% (validation)

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Table 2 (*continued*).

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[79]	2022	1 database	40 PD/40 HC		24 acoustic features (selected)	LightGBM + SVM + Spearman correlation coefficient analysis (feature importance)	LightGBM	5-fold CV; 70/30 (train/test)	**ACC**: 83.23%; **Prec**: 86.84%; **AUC**: 0.87; **Sen**: 78.57%; **Spec**: 87.95%
[80]	2023	1 dataset (train/test)	20 PD/20 HC (26 samples) - train; 14 PD/14 HC (1208 recordings) - test		39 MFCC; I-vectors extraction (GMM-UBM applied on the MFCC vectors); CNN feature extraction		(1) CNN features and MLP based system (TRAIN); (2) CNN features and SVM based system; (3) I-vectors and SVM based system	5-fold CV; Data splitting	(best) (3) SVM-poly(200) - **ACC**:97.68%; **F1-score**:0.94; **Prec**:94%; **AUC**:0.97; **Sen**:96%; **Spec**:93%
[81]	2023	1 database	50 PD/50 HC	MinMax scaling (feature scale)	PCA; MFCC features; Voice Onset Time (VOT) features; (29 features comprising 26-MFCCs, VOT, and two spectral moments)	PCA (feature selection)	FC-DNN (Adam+ReLu+binary-cross entropy (loss funtion), Tensor Flow+Softmax (class))	10-fold CV; Data splitting	**ACC**:98%; **F1-score**:0.975; **MCC**:0.97; **Sen**:97%; **Prec**:98%
[82]	2023	PDO Dataset + PD Dataset	23 PD/8 HC + 188 PD/64 HC (756 recordings)	min–max normalization	Baseline feature, time–frequency features, MFCCs, wavelet transform-based features, vocal fold features, and TWQT features	SkipConNet	SkipConNet + RF	Confusion matrix	(PD/PDO) **ACC**:99.11%/98.30%; **F1-score**:0.99/0.97; **Prec**:99/99%; **AUC**:0.9877/0.9583; **Sen**:99%/96%; **Spec**:98.77%/95.83%
[83]	2023	UCI	26 (PD+HC) + 1039 recordings	Data normalization (Min-Max Scaling)	28 features (15 features selected)	Mean Decrease in Impurity (F-MDI) (Feature importance), Feature Permutation (F-PER), Pearson's Correlation (F-CORR) techniques	NNB (hybrid KNN + GB model) (Comparison with 12 ML models)	Cross-validation; performance metrics; Data splitting	**ACC**:75.48%; **F1-score**:0.7506; **Prec**:75.63%; **AUC**:0.7492; **Sen**:74.92%
[84]	2023	PPMI database/UCI	23 PD/8 HC	Data wrangling		PCA (5 most relevant features)	3 approachs (LR, SVM, RF, KNN) (1) Models (195 records + 22 features); (2) PCA applied (195 records + 5 features); (3) Imbalance removal(109 records + 22 features)	75/25 (train/test); Performance metrics (confusion matrix)	(1) RF - **ACC**:91.83%, **Sen**:86%; (2) SVM - **ACC**:91.75%, **Sen**:86%; (3) KNN - **ACC**:91.83%, **Sen**:95%
[85]	2023	Kay Resilience Disorders Speech Database	23 PD/8 HC	Normalization	Fundamental frequency value; frequency amplitude change; Jitter; Shimmer; HNR; NHR; DFA (RPDE; D2; Spread 1 and 2; PPE)		RF (grid search method)	80/20 (train/test); Performance metrics (confusion matrix)	**ACC**:94.87%; **F1-score**:0.9359; **Prec**:96.43%; **AUC**:0.9889; **Sen**:0.9643
[86]	2023	UCI	40 PD/40 HC	Histograms	44 acoustic characteristics	Variable significance analysis (find key features)	AdaBoost; GB; Light GB; XGradient Boost	70/30 (train/test); Performance metrics (confusion matrix)	(XGB Best) **ACC**:87.39%; **F1-score**:0.8727; **Prec**:87.91%; **AUC**:0.8737 (XGB); **Sen**:87.39%
[87]	2023	Parkinson's database	55 PD/64 HC	Data augmentation technique - 1755 color spectrograms	STFT - 135 grayscale spectrograms; Feature vectors obtained from an intermediate layer of the CNN		CNN (pre-trained models: AlexNet; VGG-16; SqueezeNet; Inception V3; ResNet-50); Hybrid CNN-ELM model ((1) grayscale - original; (2) color - original; (3) color - fragments; (4) color - fragments and original	10-fold CV; 70/10/20 (train/validation/ test)	**ACC**: (1) ALX-ELM/RN5-CNN: 91.30% (2) ALX-ELM/ALX-CNN: 95.65% (3) ALX-CNN/RN5-ELM/VGG-ELM: 95.65 (4) ALX-CNN/IV3-CNN: 95.65
[88]	2023	MDVR-KCL	394 PD/615 HC (samples)	Downsampling; Sliding frame	STFT (Image of Running Speech)	DCNN	DCNN (ReLU)	756/244 (train/test) recordings; Performance measurements	**ACC**: 99.48% (training)/ 79.10% (validation)
[89]	2023	PC-GITA	50 PD/50 HC	Genetic algorithm (GA) (optimization)	WSST-based (Energy + Entropy)	Genetic algorithm (GA)	SVM and GBM	10-fold CV	SVM **ACC**:86% (vowels (/a, i/))/ 95% (isolated words (/apto/))
[90]	2023	PC-GITA + ItalianPVS	50 PD/50 HC + 28 PD/22 HC		SLT (TF spectrograms)		DNN (Relu+Softmax); (InceptionResNetV2, ResNet50V2, VGG-16)	10-fold CV	(VGG-16) (PC-GITA/ItalianPVS) **ACC**:92%/96%; **F1-score**:0.93/0.96; **Prec**:95/99%; **Sen**:92%/93%; **Spec**:91%/99%
[91]	2023	MDVR-KCL	37 PD/HC	Auto-encoder (Max-pooling, batch normalization and leaky ReLU activation functions)	Auto-encoder		SOTA model under FL strategies (FedAvg; FedAvgM; FedAdam)	60/20/20 (training-validation-test); 10 fold CV	**ACC**: 61.49% (FedAdam (0.1/0.1))
[92]	2023	1 database	23 PD/ 8 HC	Simple Imputer, Normalization		Feature selection	Hybrid Ensemble learning model (SVM+ XGBoost + LR + RF + DT)	75/25 (train/test)	**ACC**:85%–98%; **F1-score**:0.72–0.94; **Sen**: 80.5%–96%

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Table 2 (*continued*).

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[93]	2023	UCI	23 PD/ 8 HC		Pearson's correlation coefficient	Feature selection	DT + RF +LR + SVM + NB (Comparison of MLs)	70/30 (train/test); 5-fold CV; Stratified k-fold CV	RF (70-30/CV/Strat. CV) **ACC**:95.42%/91.79%/ 91.28%
[94]	2023	PD DB	160 PD/266 HC + 23PD/8HC	Data augmentation; Undersampling; SMOTE; Random oversampling	Mel-spectrograms	Information Gain (IG) ranking; Correlation-based feature selection (CFS); mRMR;	CNN Hybrid model (LSTM and GRU models)	Split data	**ACC**:93%–96% **Prec**: 84%–97%; **Sen**: 72%–98%; **F1-score**: 0.78–0.96
[95]	2023	PC-GITA + 2 datasets	50PD/50HC + 27PD/27HC + 27PD	VAD removal; Normalization	MFCC; Mel-spectrogram		ViT (Vision Transformer) (DNN model)	5-fold; training/validation split with 4:1 ratio; Confusion matrix	**F1-score**: 0.78; **Sen**: 78%; **Prec**: 77%; **AUC**: 0.83
[96]	2023	PC-GITA	50 PD/ 50 HC	Downsampled	2D recurrences plots		CNN	10-fold CV	**ACC**: 87%; **Prec**: 92%; **Sen**: 75%; **Spec**: 91%
[97]	2023	UCI + MDVR-KCL	23PD/8HC	Oversampling	PCA; Praat software; Spectrograms		SVM, CNN, DT, NB, KNN	Confusion matrix	**ACC**: 53.27–82.24%; **Prec**: 51%–89%; **Sen**: 22%–92%; **F1-score**: 0.32–0.83 (Best:DT; Worst:NB)
[98]	2023	Voice dataset + Spiral dataset	195 voice samples	Regression			Voice - XGBoost	Confusion matrix	**ACC**: XGBoost - 94%
[99]	2023	1 dataset	23PD/8HC	Standardization; Heatmap; Box Plot; Histogram plot			SVM, DT, RF, LR, Gboost, XGBoost	Split data; Confusion matrix	**ACC**:85%–87%
[100]	2023	1 dataset	188PD/64HC	Resampling	Vocal fold, TF, MFCCs, WT based and TWQT		LSTM	90(20)/10 train(val)/test	**ACC**: 93%
[101]	2023	1 dataset	40PD/40HC	Denoising (Weiner filter)	13 MFCCs		DT, KNN, RF, SVM	70/30 train/test	**ACC**: 95.8% (RF)
[102]	2023	1 dataset	23PD/9HC	Normalization; *P*-value test and Heatmap	MDVP, Jitter, Shimmer, Nonlinear measures	Feature selection	LR, KNN, DT, SVM, NB, Boosting algorithms, RF, ANN	k-fold CV	**ACC**: >72%
[103]	2023	MDVR-KCL + PC-GITA	16PD/21HC+ 50PD/50HC	Audacity audio editor software; 3s non-overlapping chunks; Normalization	1582 features (including LLD features) - INTERSPEECH 2010 paralinguistic challenge (IS10) feature set; openSMILE toolkit		LSRC and NSRC approach; SVM; RF	5/10-fold CV; 80/20 training/testing	(IS10 feature set, Proposed-NSRC) **Prec**: 81%; **F1-score**: 0.8371; **MCC**:0.47; **ACC**: 78.88%; (Combined feature set, Proposed-NSRC) **Sen**: 89.84%; **F1-score**: 0.8614; **ACC**: 82.46% ; **MCC**:0.53: (Text reading task, Proposed-NSRC)**F1-score**: 0.8103; **Prec**: 79.66%; **ACC**: 83.08%; **MCC**:0.57
[104]	2023	Kaggle	195 Rows	Data Cleaning; Normalization	23 features		XGBoost, SVM, LR	Data splitting; Grid Search CV; k-1 fold	SVM **ACC**:93%, **AUC**:0.96
[105]	2023	UCI	23PD/8HC (195 recordings)		15 voice features		Feed Forward NN		**ACC**:100%; **Prec**:100%; **Sen**:100%; **AUC**:1.00;
[106]	2023	UCI (2 datasets)	195 + 5875 rows		23 acoustic features + 22 different acoustic/motor features		LDA; KNN; DT; NN; GB;	Data splitting	(kNN) **ACC**:97.959%; **MCC**:0.93674
[107]	2023	2 datasets	756 instances (PD/HC) + 20PD/20HC + 28PD		Gender-Based Feature Analysis (GBFA); 752 features (Bandwidth, Baseline, Formants, Intensity, MFCC, TQWT, Vocal fold, Wavelet)	Classification-Based Feature scoring (CBFS); Statistical-Based Feature Scoring (SBFS); Hybrid Feature Scoring (HFS)	LSVM; NSVM; KNN; NB; RF	Data splitting; 10-fold CV	NB (9 features) **ACC**:89%
[108]	2023	CzechPD + PC-GITA + ITA + RMIT-PD datasets	16PD/16HC + 50PD/50HC + 22HC/28PD + 28PD/13HC	Data augmentation (time shift, bandpass, pitch Shift, speed change, noise addition, harmonic, normalize, volume change, resample)	STFT; log-spectrograms; 489 voice-related features; t-distributed stochastic neighbor embedding		XGBoost; DCNN	10-fold CV	ITA – CNN **ACC**:97.81%, **Sen**:99.14%, **Spec**:96.53%, **AUC**:0.9941
[109]	2023	2 dataset + PC-GITA	20PD/20HC + 38PD/40HC + 50PD/50HC		CCF-FrAT features; Spectrogram		LR; SVM; RF; MLP	LOSO; k-fold CV	(best) DB1 **ACC**:99.57%, **Sen**:99.5%, **Prec**:99.62%, **F1-score**:0.9956

Abbreviations: ACC, accuracy; ANN, artificial neural network; AO, Adam optimizer; AUC, area under curve; CNN, convolutional neural network; CV, cross validation; DDK, diadochokinetic; DT, decision tree; GA, genetic algorithm; GBM, gradient-boosting machine; GTCC, Gamma-tone cepstral coefficient; HC, healthy control; HNR, harmonic-to-noise ratio; k-NN, k-nearest neighbors; LDA, linear discriminant analysis; LFCC, linear-frequency cepstrum coefficient; LOO CV, leave-one-out cross validation; LOPO CV, leave-one-person-out cross validation; LOSO CV, leave-one-subject-out cross validation; LR, logistic regression; LSTM, long short-term memory; MAE, mean absolute error; M-BG, mini-batch gradient descent; MCC, Matthews correlation coefficient; MFCC, mel-frequency cepstral coefficients; ML, machine learning; MLP, multilayer perceptron; mRMR, minimum-Redundancy-Maximum-Relevance; NB, naive bayes; NHR, noise-to-harmonic ratio; NN, neural network; PCA, principal component analysis; PD, Parkinson's disease; PLP, perceptual linear predictive; Prec, precision; RF, random forest; RMSE, Root Mean Square Error; Sen, sensitivity; SLT, superlet transform; SOTA, state-of-the-art; Spec, specificity; STFT, short-time Fourier transform; SVM, support vector machine; TF, time frequency; TQWT, tunable Q-factor wavelet transform; UCI, University of California, Irvine; UPDRS, Unified Parkinson's disease rating scale; VAD, voice activity detection; VMD, variational mode decomposition; WT, wavelet transform; ZCR, zero-crossing rate.

Table 3
Related works - Prognosis.

Study	Year	Data		Algorithm					Performance
		Dataset	Participants	Preprocessing	Feature extraction	Feature selection	Classification		Results
							Classifier	Validation	
[110]	2019	Collected Dataset (speech, handwriting, gait) + 3 speech dataset (PC-GITA)	44 PD/40 HC (speech, handwriting,gait) + spanish: 50 PD/50 HC + german: 88 PD/88 HC + czech: 20 PD/15 HC	Praat software; OpenSMILE toolkit (speech)	MDS-UPDRS SPEECH: 88 features (EGeMAPS); 2D speech - TFR; STFT (speech and gait)		CNN; SVM	80/10/10 (training/Bayesian optimization/test); Kruskal–Wallis H-tests	**ACC**:92.3%; **AUC**:0.963 (Speech)
[111]	2021	Collected database (Spain)	36 PD	Data augmentation	CPP, D2, RPDE, MFCC5		HMM-based approach (MCMC methods)		**Global ACC**:78.29%
[112]	2022	UCI	23PD/39HC	SMOTE	MDVP software (20 features)		XGBoost; IoT called Fog based Intelligent systems	Data splitting	**ACC**:>96%
[113]	2022	Neurology Outpatient Clinic and Department of Neurology at John Paul II Hospital	27 PD (off state; 30 min; 60 min; 120 min; 180 min after medication)	Pearson and Spearman Correlation	Signal parameterization; Phonatory and articulatory analysis; 13 MFCCs; Ratio between positive and negative signal's amplitude; 13 PLP coefficients; 13 Δ PLP and 13 $\Delta\Delta$ PLP cepstral coefficients		Multiple linear regression (MLR); ϵ-SVR; RF	10-fold CV; 5-fold CV; Data splitting	**MAE**(UPDRS-III Prediction vowel /a/) RF: 1.8530
[114]	2023	1 database	42 PD (5875 voice measurements)	Imputed KNN method (check missing and imputed data); Data normalization;		BALO feature selection approach (Nonparametric Wilcoxon significant test; cross-correlation analysis)	BALO-DEELM	70/30 (train/test); Performance measures	(Sigmoid-60:UPDRS Motor/UPDRS Total) **ACC (R)**:90.82%/91.23%; **MAE**:0.400/0.395
[115]	2023	Neurology Outpatient and Department of Neurology at the John Paul II Hospital in Krakow, Poland	50 PD recordings (UPDRS-III determined)	Segmentation; Normalization	Acoustic analysis (fundamental frequency, shimmer and jitter coefficients, 12 MFCC, energy, average power, zero-order, 1^a, 2^a and 3^a order moments, kurtosis, power factor, 1st, 2nd, 3rd formant's amplitude, 1st, 2nd, 3rd formant's frequency, signal to noise ratio, max, min, mean value and standard deviation)		SVM-RBF; ϵ-SVR; GPR	10-fold CV; 90/10 (train/test)	vowel (SVM) - MAE:8.52
[116]	2023	MDVR-KCL	16 PD/21 HC	VAD algorithm (Segmentation) (658 HC; 249 HY2; 140 HY3; 39 HY4)	WS transform (Scattering)		BO approach; SVM; DT; AdaBoost; NB; KNN; MLP; LDA	80/20 (train+ validation/ test); Performance measurements; Weighted Majority Voting (WMV) (SVM, AdaBoost, KNN, MLP, LDA)	**Overall ACC**:98.62%; **AUC**: MLP: 0.98; (WMV) (HC/PDH2/PDH3/PDH4) **F1-score**: 0.9961/0.9898/ 0.9642/0.8888; **Prec**: 100/100/96.42/80%; **Sen**: 0.9924/0.98/ 0.9642/1.00; **Spec**: 1.00/1.00/ 0.9947/0.9963
[117]	2023	1 dataset	37 PD (74 samples)	Data Aggregation and Missing Data Handling; Data Normalization	PCA	RF	Hybrid RF/PCA (Correlation of Functions and Stages)		
[118]	2023	UCI	42PD	Outliers elimination (Unsupervised filters)		Correlation feature subset; Best First	Linear Regression (LR); DT; RF; GB; XGBoost	Data splitting; 10-fold CV	RF **RMSE**:1.74
[119]	2022	Finnish PD speech corpus subset + PC-GITA	35PD/15HC + 50PD/50HC	Segmentation	Speech attribute scores (SAS), Glottal, MFCC, eGEMAPS features		NN	LOSO CV	(best) (SAS+Glottal+MFCC - read) **RMSE**:11.7
[120]	2023	UCI + 1 dataset	23PD/8HC + 147PD/48HC		23 features + 22 features		OF-k-NN		Dataset1 **ACC**:97.959%; **F1-Score**:0.98; **MCC**:0.9367
[121]	2023	2 datasets	23PD/8HC + 42PD		22 features + 18 features	proposed Local dynamic feature selection fusion (LDFSF) method	GPC; RF	10-fold CV	GPC classifier (5 features) **ACC**:98.20%, **Sen**:92.00%, **Spec**:99.50%; RF regressor (8 features) **Motor-UPDRS**:1.62, **Total-UPDRS**:1.99

3.1. Datasets

Of the studies shown in Tables 2 and 3, the use of existing databases is widely observed. The most recurrent use of databases are from the UCI data repository (UC Irvine Machine Learning Repository) [122], with 33.96% (36/106) of the studies, of which the use of the Parkinson's Speech Dataset with Multiple Types of Sound Recording [123, 124], the Oxford Parkinson's Disease Detection Dataset [125–127], and the Parkinson's Disease Classification [19,128] databases can be highlighted. Two other databases can also be highlighted, given their frequency of use, these are PC-GITA [129], used in 21.69% (23/106) of the studies, and MDVR-KVL [130], used in 6.60% (7/106) of the studies.

A more detailed description of the datasets is shown in Table 4.

3.2. Preprocessing

For data preprocessing, i.e. the treatment of raw data for possible subsequent analysis [131], the use of normalization techniques is prominent, with 31.13% (33/106) of the studies implementing these technique. Segmentation and data augmentation methods are also prominent, being used in 8.49% (9/106) and 7.54% (8/106) of the studies, respectively. The Praat software [132], a software for speech

Table 4
Datasets description.

Dataset	Subjects	Type of data	Top 5 studies - Best results
Parkinson's Speech with Multiple Types of Sound Recordings [124] /Sakar et al. [123]	20 HC + 20 PD +28 PD	26 voice samples (sustained vowels /a, o, u/, numbers /1 to 10/, words and short sentences); 26 linear and time/frequency based features; UPDRS score	– [61] – ACC: 100% – SVM + MFABC + Normalization; – [27] – ACC: 100%/AUC: 1.00 – RF + IMFCC features + Downsampling; – [16] – ACC: 97.5%–100%/Sen: 100%/MCC: 0.951/Spec: 95% – NN + X^2 Statistics model + SSFH approach; – [23] – ACC: 99.94% – RF + Praat/PCA + Linear Regression/Normalization; – [42] – ACC: 99.67%/Sen: 99.35%/Spec: 99.7% – Proposed deep dual-side learning ensemble model + L1 regularization feature selection method + autoencoder
Oxford Parkinson's Disease Detection Dataset [127] /Little et al. [125,126]	8 HC + 23 PD (195 voice recordings)	Biomedical voice measurements	– [105] – ACC: 100%/Prec: 100%/Sen: 100%/AUC: 1.00 – Feed Forward NN; – [82] -ACC: 98.30%/F1-score: 0.97/Prec: 99%/AUC: 0.9583/Sen: 96%/Spec: 95.83% – RF + SkipConNet + min–max normalization; – [121] – ACC: 98.20%/Sen: 92.00%/Spec: 99.50% – GPC classifier (5 features) + proposed LDFSF method; – [71] – ACC: 97.56%/F1-score: 0.985 – LightGBM + Min-Max Scale; – [55] – ACC: 97.44%/Prec: 100%/Spec: 100%/Sen: 96.55%/F1-score: 0.9824 – KNN + Feature selection + Praat.
Parkinson's Disease Classification [128] /Sakar et al. [19]	64 HC + 188 PD	Features of voice recordings (sustained phonation of the vowel /a/)	– [82] – ACC:99.11%/F1-score:0.99/Prec:99%/AUC:0.9877/Sen:99%/Spec:98.77% – RF + SkipConNet + min–max normalization – [39] – ACC: 97.22% – Logistic Regression + voting + Autoencoder + Rescaling/min–max normalization; – [60] – ACC: 96.4%/Sen:97.1%/Spec: 98.5% – LDA (7 compressed feature vectors) + Adaptive Crow Search Algorithm; – [17] – ACC:94.89%/F1-score:0.949/Kappa value:0.894/Prec:95.1%/AUC:0.991/Sen:94.9% – RF + SMOTE; – [100] – ACC: 93% – LSTM + Resampling;
PC-GITA [129]	50 HC + 50 PD	5 Spanish vowels, diadochokinetic exercises (words and phonemes /pa-ta-ka/, /pa-ka-ta/, /pe-ta-ka/, /pa/, /ta/, /ka); words; complex and simple sentences, read text and spontaneous dialogue	– [27] – ACC: 100%/AUC: 1.00 – RF + IMFCC features + Downsampling; – [30] – ACC: 99.7% – MLP + Alexnet + Handcrafted feature-based model/Spectrograms/Mir toolbox; – [68] – ACC: 99%/AUC: 0.896/Sen: 86.2%/Spec: 93.3% – MFT CNN + STFT (spectrogram) + Data augmentation/Gaussian blurring/log-frequency spectrograms resize; – [56] – ACC: 98.61%/Prec: 96.11%/Sen: 95.93% – ResNet-LSTM network + Mel-Spectrogram + VMD method; – [51] – ACC: 97%/F1-score: 0.98/MCC: 0.96/AUC: 0.97 (word /petaka/) – SVM + STFT/Non-negative matrix factorization/TF-based feature/Baseline/Acoustic features + Downsampling.
MDVR-KCL [130]	42 HC + 31 PD (recordings)	Voice recordings (read text and spontaneous dialogue); Hoehn & Yahr (H&Y) scores, UPDRS II part 5 and UPDRS III part 18 scale	– [116] – Overall ACC:98.62% – Weighted Majority Voting (SVM, AB, KNN, MLP, LDA) + WS transform (Scattering) + VAD algorithm; – [52] – ACC:98.12%/F1-score: 0.97/Prec: 96%/Sen: 97% – CNN + RSSD/TQWT/SALSA/Time Frequency analysis/PSD + Segmentation/Noise reduction/Re-sampling; – [44] – ACC: 97.3%/AUC: 0.7232 – Resnet50-NN model + Praat + Parselmouth library; – [103] – ACC: 83.08%/F1-score: 0.8103/Prec: 79.66%/MCC:0.57 – NSRC approach + INTERSPEECH 2010 + Audacity audio editor software/3s non-overlapping chunks/Normalization; – [97] – ACC: 82.24%/Prec: 89%/Sen: 92%/F1-score: 0.83 – DT + PCA/Praat + Oversampling.

analysis, was also used to preprocess the data, but its major applications lie in the feature extraction process.

3.3. Feature extraction and feature selection

An important step in assessing the data under study is the extraction and selection of features.

For feature extraction, the techniques used can be separated into two methods: supervised and unsupervised methods [133]. In supervised methods, the data is evaluated according to certain labels and classes, depending on the properties of the data [133]. In unsupervised methods, the extraction does not consider possible tabulations, but rather possible variations and distributions of the data [133].

Tables 2 and 3 shows the use of both methods for the feature extraction phase, depending on the objective of the study, however, we can highlight the use of unsupervised methods, such as the use of Principal Component Analysis (PCA) in 8.49% (9/106) of the articles.

By analyzing the articles, it is possible to observe the use of Mel-frequency cepstrum coefficients (MFCCs), in, at least, 27.36% (29/106) of the articles, and spectrograms, in 17.92% (19/106) of the studies, as well as techniques such as the Short-Time Fourier Transform (STFT), in 9.43% (10/106) and software, like Praat [132], in 6.60% (7/106) of the articles, to assess vocal features and vocal measurements.

After extraction, the features are usually selected.

In Tables 2 and 3, 35.85% of the studies mention the use of a feature selection step.

This selection can be done using three methods [133,134]: filter, wrapper, and embedded methods.

The filtering methods consider the relevance of the data and possible similarities [133]. Some examples are in Ali et al. [16] where we can see the use of the X^2 Statistics method and in studies by Sakar et al. [19] and Fiorenza et al. [94] where the application of minimal-Redundancy-Maximal-Relevance (mRMR) is presented, both filtering methods are used to select features [133].

In wrapper methods, selection is carried out using learning models, for example the use of metaheuristic algorithms [133]. In the studies Sharma et al. [24], Soumaya et al. [57], Mohammed et al. [59] and Li et al. [61], algorithms such as Modified Grey Wolf, Genetic Algorithm and Discrete Artificial Bee Colony, are used to select the best features.

In embedded methods, the selection is made when the classifier is built, and is dependent on the classifier [134].

As with feature extraction, the three selection methods are noted throughout Tables 2 and 3.

3.4. Classification

In the data classification phase, looking at Tables 2 and 3, the use of supervised learning techniques stands out.

In this type of learning, the input data is categorized and the desired output is known. The algorithm establishes the relationships between the features supplied and the desired output, learning the different patterns [135].

Tables 2 and 3 shows the use of machine learning classifiers, in 69.81% of the studies (74/106), such as Support Vector Machine (SVM), Random Forest (RF), k-nearest neighbors (k-NN), Decision Tree (DT), Linear Discriminant Analysis (LDA), among others, as well as deep learning classifiers, 54.71% of the studies (58/106), such as convolutional neural networks (CNN), artificial neural networks (ANN), among others.

The combination of various algorithms is also observed in the same study, for example in Celik and Başaran [82], as well as comparisons between the performance obtained and algorithms usually found in the literature, for example in Wang et al. [74], and in Pramanik et al. [79].

3.5. Performance metrics

In relation to the performance of the proposed models, the use of formulas such as accuracy, sensitivity, F1-score, area under the curve (AUC), precision, and specificity are observed, with, at least, ninety-five (89.62%), fifty (47.16%), thirty-nine (36.79%), thirty-four (32.07%), thirty-two (30.18%), and twenty-six (24.52%) studies, respectively.

It is also worth noting the high accuracy values obtained, as around 83.96% of the articles obtained values of more than 80%.

4. Discussion

The main purpose of this systematic literature review was to identify, evaluate and analyze the current knowledge in the literature on the diagnosis and prognosis of Parkinson's disease through voice and speech assessment. In the subsequent paragraphs, the predefined research questions are discussed.

RQ1 - How is the problem of voice and speech assessment in Parkinson's disease addressed?

The assessment of the voice and speech of Parkinson's disease patients is performed through the analysis of voice measurements, of healthy subjects (HC) and Parkinson's disease patients (PD). These measurements can be variations in the different voice features, for example, frequencies, amplitudes, among others, which can be extracted by the authors through the analysis of voice recordings or from repository databases.

The purpose of this assessment is to diagnose (94.34% (100/106)) or prognosticate (11.32% (12/106)) the disease.

In the case of Parkinson's disease prognosis, the studies typically focus on predicting the UPDRS score [136] and the Hoehn & Yahr scale (H&Y) [137]. Twelve studies [110–121] were noted in which the prognosis of the disease is performed, although for some of them the diagnosis is also made.

In the case of diagnosis, the studies can be divided into two approaches, feature extraction and classification, i.e. part of the articles focused on finding the optimal features, while the other focused on the classifier, in order to obtain the best performance.

RQ2 - Which features are most used?

For the data classification process to be carried out with the best possible performance, it is important to take into account the choice of features to be used.

In terms of the type of recording or vocal source, that the studies presented in Tables 2 and 3 use, we can highlight the use of vowels, in at least 51% of the studies. The analysis of words, phrases, texts, monologues, and DDK exercises, whether used together, in combination with vowels, or individually, is also noted throughout the studies considered for this literature review. These voice sources are usually used to extract the chosen measurements for subsequent classification.

Looking at Tables 2 and 3, it is possible to denote a variety of features and measurements, depending on the intended purpose, but three groups of measurements can be highlighted: acoustic, time-frequency, and cepstral domain measurements. In acoustic measurements [138], jitter, shimmer, fundamental frequency values, and some voice measurements, such as HNR, among others, were observed throughout the studies. In the case of time-frequency measurements [139] and cepstral domain features [140], we can highlight the use of spectrograms and MFCCs, respectively, something already mentioned in Section 3.3.

RQ3 - What are the best classification approaches?

Analyzing the approaches illustrated in Tables 2 and 3 shows a variety of models from which different performance values are obtained.

Table 4 shows the approaches that obtained the best performance values, considering the accuracy values. These are arranged by database, and the five studies with the best results for each dataset are listed.

The use of machine learning techniques stands out compared to deep learning techniques, since more than 66% of the best approaches use these models. Among these, we can highlight models such as RF and SVM, with values of 100% having been obtained in research that has made use of them, for example in [27,61].

Nevertheless, this does not detract from the success of deep learning techniques since their good performance is also notable, for example, in the studies [105,30] in which deep learning models were used and achieved accuracy values of 100% and 99.7%, respectively, which demonstrates their high degree of effectiveness.

Of the studies mentioned in Table 4, it should be emphasized that more than 90% of the approaches obtained an accuracy value of more than 93%, with the remainder having a minimum value of 82%, which indicates the ability of the proposed models to diagnose and/or prognosticate Parkinson's disease with a good success rate.

RQ4 - What are the main limitations and future possibilities found in the field?

One of the main limitations observed is in relation to the type of data used. As mentioned above, the vast majority of the data used is from repositories, where the data is acquired in controlled environments, i.e., noise and other types of external interference are very small or even non-existent, something that would not happen if real-data was used, for example, data acquired in clinical contexts, where absolute control of the surrounding environment is not possible.

Another limitation that can be pointed out, also related to the data, is the language that the subjects speak. The majority of studies use databases in English or Spanish, although there are also studies with data in languages such as Turkish, Czech, German, Chinese, Finnish, and Portuguese, among others, these are limited. So, the fact that the vast majority of studies only analyze data in these languages could be an obstacle to analyzing patients who speak other languages.

Therefore, taking into account the limitations presented, in terms of future possibilities, we can point to the formulation of models with real-data and also for different languages, thus covering more patients. This could be advantageous for future application in clinical contexts, where the diagnosis and prognosis of Parkinson's disease is carried out.

Limitations of the review

Certain limitations were encountered in this systematic literature review, of which the following can be emphasized: (1) the use of only the SienceDirect, the IEEE Xplore, and the ACM Library databases, mentioned in Table 1, and the non inclusion of other databases such as the PubMed, among others, which may have limited the search for articles to be included in this research; (2) the keywords used, which may have led to a limitation in the search for studies; (3) some articles were excluded due to a lack of detail about the data and techniques they used; (4) only articles in english were considered.

5. Conclusions

This systematic literature review presents a summary of current approaches to the diagnosis and prognosis of Parkinson's disease through voice and speech analysis using machine learning techniques. Thus, by analyzing the 106 articles included, it was possible to answer the research questions initially set.

- (RQ1) The voice analysis using machine learning techniques for the diagnosis and prognosis of Parkinson's disease has been growing in recent years. In general, it can be summarized as the assessment of recordings or measurements of voice or speech, followed by classification by a machine and/or deep learning model.
- (RQ2) With regard to the voice features/characteristics used, the vast majority focus on evaluating features related to the time-frequency domain, cepstral domain, or acoustic characteristics/measurements.
- (RQ3) With regard to the best approaches, some deep and machine learning models stand out in terms of performance obtained, something that illustrates the possibility of voice analysis with the intention of diagnosing and prognosticating Parkinson's disease with satisfactory results.
- (RQ4) The limitations listed are in relation to the data used, although there may be other types of limitations not mentioned in this review. Future possibilities could include improving the approaches so that they can be applied in clinical and hospital contexts.

Through this review of the literature, it is possible to draw some conclusions about future research and a possible future in clinical practice. Such as: (1) the identification of preexisting databases on Parkinson's disease; (2) the identification of features/characteristics found in the voice and speech of PD patients used for the diagnosis, detection or prognosis of the disease; (3) the identification of techniques used for preprocessing, for the extraction and selection of features, and for classification and validation through the voice of Parkinson's disease patients.

These findings may help in the formulation of new studies in this area. Something that could, in the near future, lead to (4) earlier diagnoses, without being based solely on the patient's 'visible' symptoms; (5) which can also leads to a more reliable prognosis, which could be an asset for the definition of the treatment to be applied and consequently trying to improve the patient's well-being.

Finally, it should be noted that this systematic literature review only covered studies from a period of five years that are available in the three databases mentioned, so there are certainly more studies and approaches that have not been mentioned, and it should also be noted that only English-language studies were included.

CRediT authorship contribution statement

Daniela Xavier: Writing – original draft. **Virginie Felizardo:** Writing – original draft, Supervision. **Beatriz Ferreira:** Writing – original draft. **Henriques Zacarias:** Writing – original draft. **Mehran Pourvahab:** Writing – original draft. **Leonice Souza-Pereira:** Writing – original draft. **Nuno M. Garcia:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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