Method for Detecting Subliminal Parkinsonian Deficits based on Automatically-analyzed Speech Features Data

Jinghan Zhao *

College of Life Science and Technology, Huazhong University of Science and Technology, Wuhan, 430074, China

* Corresponding author: jhzh12510@hust.edu.cn

Abstract. Parkinson's disease (PD), one of the most prevalent and well-known neurodegenerative disorders, has raised great concern in society. For many years, sensory testing has been the only method used to assess speech deficits in neurodegenerative diseases like PD. Therefore, by mining an automatically-analyzed speech dataset, a model was developed and an attempt was made to separate PD patients and RBD patients from general population. The acoustic features involved in this study included timing, articulation, phonation, and respiration, which were collected and analyzed based on recordings of participants reading a passage. The model was able to identify the patient's speech deficits by recognizing variations between the samples. According to this study, patients with related neurodegenerative disorders could suffer from a certain pattern of speech abnormalities that enables them to behave differently from healthy controls. This approach is intended to provide researchers with thoughts for future research into speech deficits and possible treatments associated with neurodegenerative illnesses.

Keywords: Parkinson’s disease, speech, logistic regression, data mining.

1. Introduction

Up to 10 million people throughout the world are thought to be affected by Parkinson's disease (PD), a well-known neurological condition [1]. Patients' lives and health are gravely endangered, and a significant number of medical resources are consumed [2]. According to epidemiological research, there is roughly one diagnosis every hour and a global prevalence of 200/100,000 [3].

The preclinical course of PD has received extensive attention recently. Finding vocal deficiencies therein is a challenging and research-worthy subject. Patients suffer from complicated underlying symptoms, such as rigidity, tremor, akinesia, and bradycardia. Apart from that, they showed signs of supporting motor impairments, including difficulty with gait, slurred speaking, impaired grip strength, and handwriting trouble [4]. The vast majority of PD patients experience hypokinetic dysarthria in particular. Such individuals frequently exhibit characteristics including diminished voice, motor hypophonia, mono-pitch, monoloudness, and timing deficiencies. Speech and voice anomalies that are perceptibly distinct are how this condition presents [5].

Studies have found that motor fluency in PD patients is specifically impaired in the early stage of the disease, while semantic and speech fluency is gradually impacted over time [6]. Clinically, it is typical for most PD patients to have a lower voice volume and shorter average and maximum sustained vowel pronouncing durations [7]. The prior study concentrated on enhancing patients' speech and language abilities. A speech therapy method known as Lee Silverman Speech Therapy (LSVT) was developed, and it has shown a significant increase in transcripts in PD patients from baseline to post-treatment [8]. Ultrasonic vocalization (USV) is examined to look at alterations in vocal communication [9]. The intrinsic laryngeal muscles are activated, the vocal tract is modulated during exhaled airflow, and airflow is generated by raised pulmonary pressure are all characteristics of USV [10]. USV can be utilized to examine the sensorimotor regulation of speech in PD models since they resemble human vocalization. Prior research has primarily concentrated on patients receiving treatment in the middle or late period of PD. The study of voice during the incubation period before the emergence of major PD symptoms, however, continues to face significant limitations [5].

Rapid eye movement sleep behavior disorder (RBD) is an episodic disorder characterized by loss of muscle relaxation and complex movements associated with dreams. There are currently no prodromal indicators for predicting RBD, despite the fact that people with RBD have a significant probability of contracting PD or other neurodegenerative illnesses. Research on prodromal speech abnormalities in RBD patients is lacking, nevertheless. As a result, the major goal of this study is to determine if patients with RBD and PD have a similar pattern of Parkinsonian language impairment.

It is essential to identify the biomarkers linked to neurodegeneration because they can offer important insights into prognosis, treatment, clinical trials, and disease-modifying medicines before motor function [5]. The technique involves establishing a relationship between acoustic speech features and disease states. Acoustic speech feature data comprises connected speech with fundamental physiological roots. Participants are separated into different groups according to their personal illnesses. Logistic regression and k-nearest neighbors' algorithm will be applied with their acoustic speech features for performing training process. The method enables performing data analysis and comprehensive analysis on disease data, and improving prediction precision on identifying biomarkers related to neurodegeneration.

2. Methods

2.1. Data Description

In the dataset, the total number of participants is 130. Patients included fifty people with RBD and thirty people with untreated PD. 50 healthy adults without a history of neurological or communicative issues were also present.

Baseline characteristics (Table 1) include demographic information, clinical information, and overview of motor examination. Neurologists with experience and knowledge of movement disorders identified and evaluated clinical scales [5].

Table 1. Basic characteristics of participants

Characteristics	PD (n=30)	RBD (n=50)	HC (n=50)
Mean age (years)	64.9 (SD 10.9, range 34–79)	64.9 (SD 9.1, range 40–83)	64.9 (SD 9.4, range 34–83)
Mean age of onset (years)	63.4 (SD 11.9, range 30–78)	59.2 (SD 9.8, range 33–81)	-
Mean symptoms duration (years)	1.6 (SD 1.3, range 0.5–6)	5.8 (SD 4.4, range 1–17)	-
Mean Hoehn & Yahr score	2.1 (SD 0.3, range 1.5–2.5)	-	-
Mean UPDRS III total	20.2 (SD 12.4, range 6–54)	5.2 (SD 4.1, range 0–21)	-
Mean UPDRS III speech item	0.4 (SD 0.5, range 0-1)	0.06 (SD 0.24, range 0-1)	-

The Unified Parkinson's Disease Rating Scale motor subscale (UPDRS III) was used to grade PD and RBD patients. UPDRS III ranges from 0 to 108, with low to high scores representing mild to severe defects. The Hoehn & Yahr score, which was developed by Margaret Hoehn and Melvin Yahr and published in Neurology in 1967, uses a scale of 1 to 5 stages to grade the dysfunction related to Parkinson's disease.

The initial researchers developed and published a completely automated voice monitoring system for this investigation. Briefly, each participant was required to read and reread an 80-word essay. The concatenated speech is automatically segmented by the algorithm, and the findings are used to create a set of 12 acoustic signatures. These characteristics enable evaluation of all essential interrelated speech subsystems, such as timing, phonation, articulation, and respiration [5]. These features are chosen to be the variables examined in this method, and their descriptions are shown in Table 2.

Further details regarding data collection and principles of data analysis can be found in the original publication.

Table 2. Variables selected in the database

Aspect	Variable name	Description
Timing	EST	Entropy of speech timing (-)
	RST	Rate of speech timing (-/min)
	AST	Acceleration of speech timing (-/min^2)
	DPI	Duration of pause intervals (ms)
Phonation	DVI	Duration of voiced intervals (ms)
	GVI	Gaping in-between voiced intervals (-/min)
Articulation	DUS	Duration of unvoiced stops (ms)
	DUF	Decay of unvoiced fricatives (‰/min)
Respiration	RLR	Relative loudness of respiration (dB)
	PIR	Pause intervals per respiration (-)
	RSR	Rate of speech respiration (-/min)
	LRE	Latency of respiratory exchange (ms)

2.2. Research Methods

2.2.1. Logistic regression

A logistic model is used to simulate the likelihood that an event will occur by transforming the log odds of an event into a linear combination of independent factors. In regression analysis, logistic regression is used to estimate a logistic model's parameters.

N points make up the dataset that is presented. A set of input variables and a binary outcome variable make up each point. Using a data set, logistic regression aims to develop a prediction model of an outcome variable. The outcome variable is considered to depend on the explanatory variables, just like in linear regression. In this paper, the binary variable will be “diseased or not”, where PD and RBD patients are defined in the same class. At the same time, the healthy control group will appear as the opposite category.

2.2.2. K-nearest neighbors algorithm

K-nearest neighbors (k-NN) is an unsupervised machine learning algorithm. Training examples are categorized as classes, specified as vectors, and put in a multidimensional feature space. The algorithm stores the class labels and features of the training data. Query points, or unlabeled vectors, are categorized using the user-defined constant k during the classification phase. The class label of the query point is determined by the k training samples closest to the query point location.

3. Results and Discussion

Consistent with established Machine Learning practices, the dataset is separated into ‘training’ and ‘testing’ sets. Approximately 80% of the total observations are in the training dataset, while about 20% are in the testing dataset. Stratified sampling is applied in the segmenting procedure, with a sampling fraction in each of the strata (diseased or not) that are proportional to that of the total observations. All variables are transformed by centering and scaling. This method of data transformation focusses on variables with a mean of 0, and scales them to have a standard deviation of 1. This approach unifies the standard for linear combination and improves numerical stability by performing data scaling based on how much variation is occupied by variables.

Models based on logistic regression or k-nearest neighbors’ algorithm are constructed through RStudio software. In order to choose the best model, regression models are used to predict the validation data. The accuracy of the models is then calculated. Lastly, using the test set to gauge model performance, the best model derived from the training and validation sets is applied for prediction.

3.1. Model Validation Results

The training set is used to build the model. To choose the best model, a 10-fold validation is applied to the training set. The two models' prediction results of the validation set are then acquired, as well as the equation of logistic regression model and the k value of k-NN regression model. Table 3 presents resampling results with different k value. The logistic regression equation is represented by Equation (1) and Equation (2). The modeling results are presented in Table 4.

3.1.1. Logistic regression

The model for conducting predictions for the odds can be expressed as follows:

$$\mathrm{Y} = -0.853 + (-0.608) * \mathrm{EST} + 1.786 * \mathrm{RST} + 0.079 * \mathrm{AST} + (-1.190) * \mathrm{DPI} + 1.102 * \mathrm{DVI} + (-0.986) * \mathrm{GVI} + (-0.042) * \mathrm{DUS} + (-0.156) * \mathrm{DUF} + (-1.085) * \mathrm{RLR} + 0.747 * \mathrm{PIR} + 0.687 * \mathrm{RSR} + 0.916 * \mathrm{LRE} \quad (1)$$

The logit or log-odds function, which appears in the formula as Y on the left, is defined as follows:

$$\log\left(\frac{p}{1-p}\right) = \mathrm{Y} \quad (2)$$

The odds are the ratio of the chances of success to the chances of failure. The p is the predicted output, which represents the probability of having the disease, ranging between 0 to 1.

3.1.2. K-nearest neighbors algorithm

The optimal model of k-NN regression is selected by the largest accuracy.

Table 3. Resampling results across tuning parameters

k value	Accuracy
5	0.6364
7	0.6345
9	0.6154
11	0.6164
13	0.6245

According to Table 3, the final value used for the model is k=5. An unlabeled vector is classified by applying the label that occurs most frequently in the five training samples nearest to the test point.

Table 4. Comparison of predictive performance of regression models

Regression models	Accuracy
Logistic regression	0.6782
k-NN regression (k=5)	0.6364

Table 4 shows that the logistic regression model with the larger accuracy is the optimal model. In the following stage, the disease status is predicted by applying the logistic regression model.

3.2. Model Test Results

The receiver operating characteristic (ROC) curve is depicted in Fig. 1 according to the predicted outcomes of 27 individuals, and the AUC is 0.606. Furthermore, the prediction model's accuracy is 0.654. The classification outcomes of the discriminant analysis are displayed in the confusion matrix in Fig. 2. 17 samples (13 diseased, 4 healthy) are predicted correctly, 6 healthy samples are predicted false positive, and 3 diseased samples are predicted false negative.

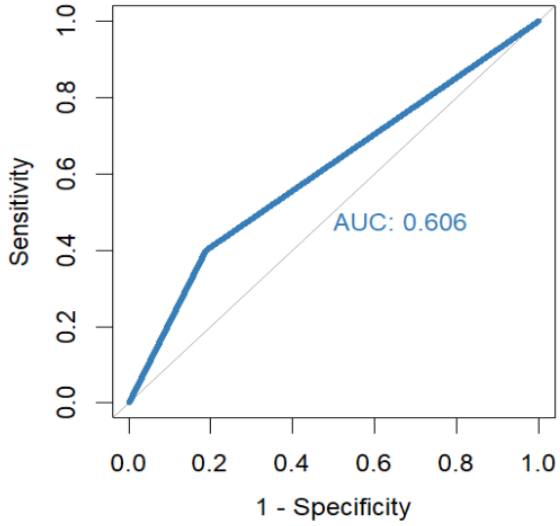


Figure 1. ROC curve analysis of the model

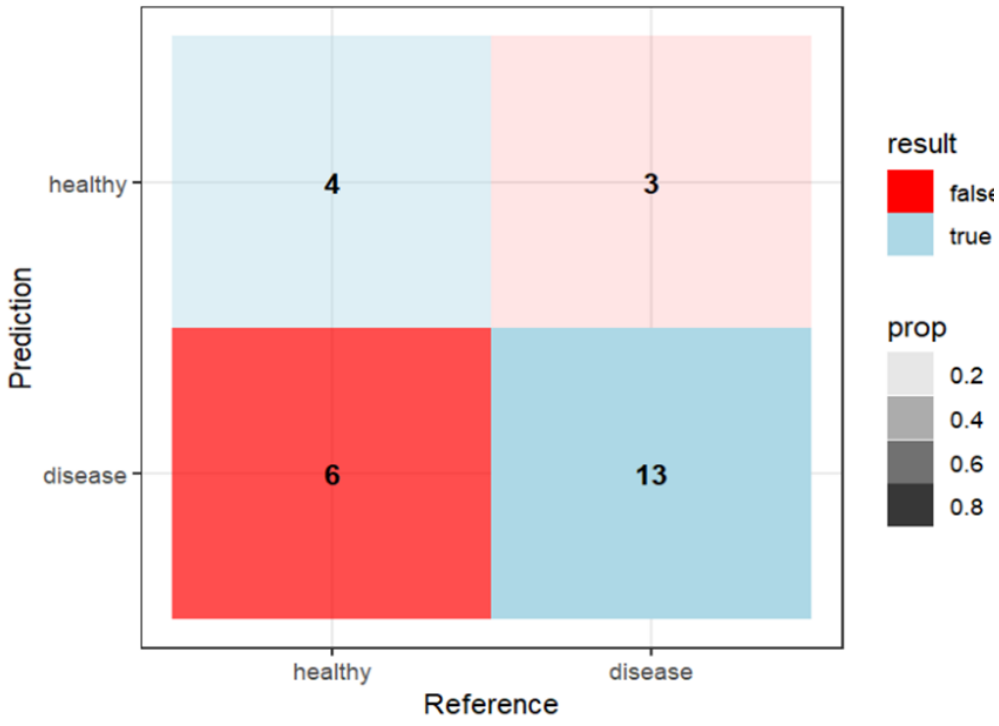


Figure 2. Confusion matrix of the model

The model has a relatively high sensitivity (0.8125), indicating a potent capacity to recognize patient patterns of acoustic deficits. However, the specificity of the model is limited (0.4000), tending to predict healthy control samples as diseased.

3.3. Discussion

In this approach, PD and RBD patients are combined into one group, and the speech characteristics that differentiate them from healthy participants are examined. Since the model is able to distinguish patients from healthy individuals to a certain extent, it can be speculated that PD patients or those at risk of developing related neurodegenerative diseases have similar speech characteristics. Though the UPDRS III speech item in Table 1 revealed that the majority of RBD individuals had no discernible speech impairment, it's interesting to note that both PD and RBD subjects objectively exhibit the same speech irregularities.

Nocturnal phasic activities have been studied in patients associated with RBD. The motor and vocal activities that are amplified during REM sleep have been found to vary greatly among subjects and between nights. However, little research has been done on how well patients with RBD perform on general speech tasks, such as spontaneous speech, reading passages, or text-dependent utterances. Additionally, research has been done on the multilingual evaluation of biomarker composite arrays. Participants with PD produced speech that was shorter in overall length, word count, nouns, auxiliary verbs, and noun phrases. As a result, the study sheds light on how PD can be objectively assessed using language and speech. The closeness of speech features between RBD and PD patients is yet unsupported by experimental or clinical research, nevertheless. This approach can only speculate, based on the model classification findings, that these patients vary from healthy individuals and share certain acoustic characteristics. The underlying mechanisms of potential acoustic abnormalities in RBD patients should be the subject of additional study to determine whether they are related to the emergence of PD.

The outcomes and conclusions reached thus far need to be improved due to the method's limitations. The participants in the studied dataset ranges in case severity, and the sample size is limited (n = 130). Similarly, it could be challenging to address general problems in healthy populations. Due to this circumstance, the model's accuracy must be increased, and further research into its use in the early Parkinson's disease diagnosis and prediction is required.

Additionally, patients should be further categorized in accordance with the severity of the illness, for instance, by concentrating on various PD subgroups. To identify subtypes, utilize H&Y Score or UPDRS. The identification of early acoustic indicators may aid in the earlier diagnosis of PD and the tracking of the disease's progression. Different subtypes of language impairment can be seen among various PD subgroups. The understanding of the mechanisms that cause speech deficiency in PD is anticipated to improve when considering the severity and duration of the disease. Decisions on upcoming speech-language therapy may also be influenced by such findings.

4. Conclusion

This study analyzed the speech characteristics of PD patients, RBD patients and healthy controls, developed a model and intended to use these data to distinguish patients from healthy controls. The objective was to investigate potential acoustic abnormalities shared by patients with PD and RBD. The outcomes of the model classification suggest that patients' speech features may have some traits that set them apart from healthy individuals. To increase the precision of the model, more thorough research has to be conducted.

It is envisaged that this approach may give researchers in the future concepts for investigating voice deficiencies and their treatments related to neurodegenerative disorders. The sample size needs to be expanded to account for multiple factors, including age, language category, and disease severity. The ultimate goal of related research is to aid in the diagnosis and treatment of PD. Examples of this assistance include performing speech-related treatments for PD patients or screening people in the population who may be at risk for the condition. It is also necessary to elaborate on the acoustic features. The processing of relevant variables can be improved in future studies to enable an in-depth investigation of this issue.

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