Journal of Ambient Intelligence and Humanized Computing (2023) 14:13571–13584
https://doi.org/10.1007/s12652-022-03825-w

ORIGINAL RESEARCH

Prediction of Parkinson's disease based on artificial neural networks using speech datasets

Wei Liu[1,3] · Jierong Liu[2] · Tao Peng[2] · Guojun Wang[2] · Valentina Emilia Balas[4] · Oana Geman[5] · Hung-Wen Chiu[6]

Received: 23 August 2020 / Accepted: 10 March 2022 / Published online: 12 April 2022

Abstract

Parkinson's disease (PD) is a progressive disorder of the nervous system that affects movement. Early prediction of PD can increase the chances of earlier intervention and delay the onset of the disease. Vocal impairment is one of the most important signs in the early stages of PD. Therefore, PD detection based on speech analysis and vocal patterns has attracted significant attention recently. In this paper, we propose a vowel-based artificial neural network (ANN) model for PD prediction based on single vowel phonation. Firstly, we propose a novel multi-layer neural network based on speech features to predict PD. The speech samples from 48 PD patients and 20 healthy individuals are processed into four types: vowel, number, word, and short sentence. Secondly, we establish ANN models with single-type speech samples versus combinations of multi-type speech samples, respectively. Comparative experiments demonstrate that the single-type vowel model is superior to other single-type models as well as multi-type models. Finally, we build a vowel-based ANN model for PD prediction and evaluate its performance. Extensive experiments demonstrate that the proposed model has a prediction accuracy of 91%, sensitivity of 99%, specificity of 82%, and area under the receiver operating characteristic curve (AUC) of 91%, which is superior to the performance of previous methods. Overall, this study demonstrates that the proposed model can provide good classification accuracy for predicting PD and can improve the rate of early diagnosis.

Keywords Artificial neural network · Parkinson's disease · Clinical decision support · Vowel

Abbreviations

PD	Parkinson's disease
ANN	Artificial neural network
AUC	Area under the receiver operating
ROC	Receiver operating characteristic characteristic curve
RF	Random Forest
SVM	Support vector machines
K-NN	K-Nearest neighbor
LOSO	Leave-one-subject-out
CV	Cross validation
PCA	Principal component analysis
LDA	Latent Dirichlet allocation
MFCC	Mel frequency cepstral coefficient
DNN	Deep neural network
UPDRS	The unified PD rating scale
ADL	Activities of daily life
MLP	MultiLayer perceptron
DA	Dopamine
L–M	Levenberg–Marquardt
TP	True-positive
TN	True-negative
FP	False-positive
FN	False-negative

✉ Tao Peng
pengtao@gzhu.edu.cn

1 School of Information and Communication Engineering, Hainan University, Haikou 570228, Hainan, People's Republic of China

2 School of Computer Science and Cyber Engineering, Guangzhou University, Guangzhou 510006, Guangdong, People's Republic of China

3 College of Biomedical Information and Engineering, Hainan Medical University, Street, Haikou 571199, Hainan, People's Republic of China

4 Department of Automation and Applied Informatics, Aurel Vlaicu University of Arad, 310130 Arad, Romania

5 Department of Health and Human Development, Stefan cel Mare University of Suceava, 720229 Suceava, Romania

6 Graduate Institute of Biomedical Informatics, Taipei Medical University, Taipei, Taiwan

1 Introduction

Parkinson's disease (PD) (Gupta et al. 2018b; Bastiaan et al. 2021) is a neurological disorder that is more common in the elderly than in the general population. PD can cause tremors, stiffness, and problems with walking, balance, and coordination. As these symptoms become more pronounced, patients may have difficulty in walking, speaking, or completing other simple tasks. Early detection and treatment of PD can help control the progression of the disease, relieve symptoms, and improve patients' quality of life. Vocal change in PD patients is a promising biomarker in the early stages of PD. Using machine learning (Sangaiah et al. 2020a, b) to recognize patients' speech alterations can help diagnose PD in its early stages (Mostafa et al. 2018; Gupta et al. 2018a; Mostafa et al. 2019). Recently, PD detection based on speech analysis and vocal patterns has attracted significant attention (Pereira et al. 2019). Voice remote monitoring can be easily achieved without invading the patient's body. In addition, speech analysis methods typically do not require continuous observation of patients, which means that patients do not need to be hospitalized. Thus, the voice signal has the advantages of convenient collection, low loss, low cost, and high user acceptance (De Keyser et al. 2016).

In recent years, researchers have proposed various methods to detect PD using acoustic analysis of voice signals. Most studies focus on speech signal processing techniques to obtain clinically relevant features, and various machine learning algorithms to obtain reliable classification accuracy. For example, Tsanas et al. (2012) presented a methodology that enabled the establishment of the 10 best features to identify patients with signs of PD. They used a database of 263 samples from 43 individuals to compute over 132 dysphonia measures from sustained vowels, using Random Forest (RF) and support vector machines (SVM) to build the statistical classifier. Sakar et al. (2013) collected and analyzed multiple types of voice recordings from 40 subjects out of which 20 were healthy subjects and 20 were PD patients. They used SVM and K-nearest neighbor (K-NN) models and achieved mean accuracy of 55% using leave-one-subject-out (LOSO) cross validation (CV).

While SVM, RF, and K-NN are the common algorithms in PD classification due to their simplicity and also ease of understanding, the classification accuracy needs to be improved. Additionally, speech communication varies from culture to culture. Even within a single language or a language group, there are differences in intonation and pronunciation. Compared with multiple types of samples, we believe that a single-type of pronunciation may perform better.

In the previous study (Chiuchisan et al. 2014; Geman and Chiuchisan 2015; Toderean et al. 2016), we have established suitable and effective protocols for the acquisition of signals to exploit the dynamics of hand or leg movement considering tremors, handwriting, and speech for PD patients monitoring. On the basis of it, we will continue to invest a method from subjects to help the development of noninvasive prediction and treatment of PD. In this paper, we propose a realistic and effective artificial neural network (ANN) model based on single vowel phonation which is capable of maintaining high accuracy. The main contributions of this paper can be summarized as follows:

1. We propose a novel multi-layer neural network based on features of voice, which has higher stability, robustness and efficiency of achieving the maximum classification performance, when compared to other advanced machine learning methods such as SVM and CNN.
2. We suggest a new distinctive classification method that proposes to apply a unique classifier to single-type vowel samples instead of multi-type ones, such as number, word, short sentence, or combined pronunciation.
3. We propose a vowel-based ANN model based on single vowel phonation to predict PD, which can facilitate more comfortable and timely prediction of PD, and evaluate its performance. Simulation results demonstrate that the proposed model can provide good classification accuracy for the prediction of PD and can improve the rate of PD early diagnosis.

The remainder of the paper is organized as follows: Sect. 2 outlines related work. Section 3 describes how our study is performed, including an overview of current PD evaluation procedures and a description of the ANN model. This section also describes data processing and the methods used for constructing the proposed model. Section 4 discusses experimental results in detail and provides a high-level summary of our findings. Section 5 presents our conclusions and discusses possible directions for future work.

2 Related work

Recently, researchers have found that voice signals recorded from PD patients are useful to differentiate them from healthy individuals. It has been determined that almost all PD patients have some degree of speech disorder due to complication-induced vocal cord damage.

Traditional machine learning classifiers such as SVM, RF, and K-NN have been applied to PD prediction. For example, Malathi et al. (2019) proposed a hybrid reasoning-based methodology that combines fuzzy sety theory, K-NN and case-based reasoning on predicting diseases. Traditional

machine learning methods and their combinations can improve the accuracy of disease prediction. Tsanas et al. (2012) proposed a PD detection model with vocal features and applied several feature selection techniques to select the top 10 features with high relevance scores as the inputs of such model. The performance of the selected features was up to 98.6% of precision rate, using RF and SVM to build the statistical classifier. Sakar et al. (2013) collected and analyzed multiple types of voice recordings from 40 subjects out of which 20 were healthy subjects and 20 were PD patients. They used SVM and K-NN models and achieved mean accuracy of 55% using LOSO CV. Caesarendra et al. (2014) proposed a PD multilevel classification pattern recognition method based on principal component analysis (PCA), latent Dirichlet allocation (LDA), and SVM. A total of 22 speech features were extracted using PCA and LDA. These features were then used by the SVM for speech classification. Li et al. (2017) used hybrid feature learning and SVM for classification and achieved an accuracy of 82.5%. Benba et al. (2017) selected different features iteratively and applied the subset of the selected features to SVM for classification. They achieved a classification accuracy of 82.5% for LOSO CV. Soumaya et al. (2020) proposed a model of classification by the use of a discrete wavelet transform to transform the signal. They achieved an accuracy of 91.18% with a reduced vector of 15 features, and a vector of the 20 first mel frequency cepstral coefficient (MFCC) features used with multilayer perceptron (MLP), and linear kernels of SVM gave an accuracy of 80% and 72.5%.

Another popular and powerful classifier is ANN. Berus et al. (2019) used multiple feed-forward ANNs with various configurations to predict PD in individuals based on features extracted from 26 different voice samples. Ali et al. (2019) used the LDA model for dimensionality reduction and the neural network model for classification. The architecture of the neural network model was optimized using a genetic algorithm. They obtained 80% accuracy on the training database and 82.14% on the testing database.

Since deep neural network (DNN) has the potential to model complex and non-linear relationships from data, it is also an advisable classifier for PD prediction. Deperlioglu et al. (2020) proposed that the accuracy rate of diagnosis (classification) can be improved via deep learning algorithms, not needing hybrid-complex models. Classification of heart sounds with autoencoder neural networks and the application of 479 real-case have been found positive by the doctors, which suggested that more consideration should be given to practical usability when applying DNN for predictive classification in clinical decision-making. Frid et al. (2016) used rough-set methods for feature selection and leveraged the self-training characteristics of convolutional networks. Specifically, they used the characteristics of convolution kernel storage and constant update and adjustment of learning capabilities to generate intermediate features for their network, which was comprehensively analyzed based on the results of intermediate feature outputs. To enhance classification accuracy, different feature selection algorithms have been proposed. Gunduz (2019) proposed two frameworks based on CNNs to classify PD using sets of vocal (speech) features and achieved an accuracy of 86.9%.

When examining the aforementioned studies, it is clear that earlier PD prediction studies generally use voice features with machine learning algorithms. Although various methods have been developed for the prediction of PD, their ease of use and stability are unsatisfactory. Among them, the most widely used classification techniques are SVM, ANN, and DNN. SVM is usually applied to multiple classification problems, and it can be stated that SVM-based models have been widely used in PD prediction, showing their robustness. However, there is no advantage to use SVM compared to an ANN classifier. ANN learning algorithm, which can decide on new instances via establishing connections between the training examples, is widely used in solving various classification and non-linear problems. By providing decision-making to clinicians, it can provide faster and more effective and contribute to accuracy. DNN gives promising results by modeling highly complex data with high accuracy, but the black-box nature is a drawback in practical deployment. Therefore, ANN is the most suitable learning algorithm for PD prediction. Moreover, mixing different pronunciation types in vocal tests can lead to confusion of valuable information and reduce the prediction accuracy. To solve this problem, we try to develop a realistic and effective ANN model with the simplest pronunciation for discriminating PD patients from healthy individuals and maximize the accuracy of proposed method.

3 Methods and materials

3.1 Assessment of PD

Our proposed method uses Unified Parkinson's Disease Rating Scale (UPDRS) (Fish 2018) as the standard PD metric, which is the most widely accepted clinician-scored monitored motor evaluation. The most important pathological change in PD patients (Rizek et al. 2016) is the degeneration of dopamine (DA) neurons in the midbrain, which causes a significant decrease in striatum DA content. The exact cause of this pathological change remains unclear. Genetic factors, environmental factors, aging, and oxidative stress may be involved in the degenerative death of PD dopaminergic

neurons. The main clinical manifestations of PD are resting tremors, bradykinesia, myotonia, and posture/gait disorders.

The UPDRS, which was developed by Fahn et al. in 1987, is used to monitor the longitudinal course of PD. It includes signs, symptoms, and drug-related fluctuations. The UPDRS focuses on three aspects of patient health: mental state, daily living ability, and exercise index. Each aspect is divided into five levels with indexes of zero to four, where zero represents "normal" and four represents "severe". The UPDRS consists of the following sections (on Rating Scales for Parkinson's Disease 2003):

Part I: Evaluation of mentation, behavior, and mood.

Part II: Self-evaluation of the activities of daily life (ADL), including speech, swallowing, handwriting, dressing, hygiene, falling, salivating, turning in bed, walking, and cutting food.

Part III: Clinician-scored monitored motor evaluation.

Part IV: Complications of therapy.

Part V: Hoehn and Yahr staging of severity of PD.

Part VI: Schwab and England ADL scale.

Patients are typically evaluated in clinical settings through interviews and clinical observations. Both clinicians and researchers use UPDRS and exercise components to track the progression of human PD (Robert et al. 2018). Scientific researchers use it to measure the benefits of a given therapy based on a uniform and accepted rating system. Over time, UPDRS scores can provide insights into a patient's disease progression.

3.2 Artificial neural network

In the proposed efforts, ANN is used to establish models with various voice types and maximize the PD prediction accuracy. ANN (Amato et al. 2013), which is an artificial network consisting of a large number of interconnected processing units (neurons), can simulate the structures and functions of the brain. Based on their strong nonlinear mapping ability, ANN can induce rules from known data automatically and derive the inherent laws of data. By learning sample data, knowledge is stored in the network in the form of weights and thresholds (Pérez-Sánchez et al. 2018). Based on its powerful learning and processing abilities, ANN has provided a new theoretical method for the prediction and treatment of PD. ANN is adopted to approximate the nonlinear mappings of inputs (e.g., speech signals) in our study. Based on their adaptive characteristics, neurons can learn and recognize patterns in inputs and produce appropriate output values depending on inputs and activations (Lahmiri et al. 2018). The Levenberg–Marquardt (L–M) algorithm (Ardiansyah et al. 2016) is one of the most effective neural network training procedures and yield good performance for training neural networks in our study. The L–M algorithm is a combination of the Gauss–Newton and steepest descent methods. It is very suitable for neural network training, where the main performance index is a mean-squared error.

The optimizing performance index $F(x)$ in Gauss–Newton method is $X_{k+1} = X_k - A_k^{-1} g_k$, where $X_k = \Delta^2 F(x) \mid X = X_k$, $g_k = \Delta F(x) \mid X = X_k$. Assume $F(x)$ be the sum of the square functions, then

$$F(x) = \sum_{i=1}^{n} V_j^2(X) = V^T(X)V(X) \tag{1}$$

The gradient can be presented as:$\Delta X_k = -[J^T(X_k)J(X_k) + \mu_k I]^{-1} J^T(X_k)V(X_k)$, here

$$J(X) = \begin{Bmatrix} \frac{\vartheta_{v_1}(x)}{\vartheta_{x_1}} & \frac{\vartheta_{v_1}(x)}{\vartheta_{x_2}} & \cdots & \frac{\vartheta_{v_1}(x)}{\vartheta_{x_n}} \\ \frac{\vartheta_{v_2}(x)}{\vartheta_{x_1}} & \frac{\vartheta_{v_2}(x)}{\vartheta_{x_2}} & \cdots & \frac{\vartheta_{v_2}(x)}{\vartheta_{x_n}} \\ \cdots & \cdots & \cdots & \\ \frac{\vartheta_{v_N}(x)}{\vartheta_{x_1}} & \frac{\vartheta_{v_1}(x)}{\vartheta_{x_N}} & \cdots & \frac{\vartheta_{v_N}(x)}{\vartheta_{x_n}} \end{Bmatrix} \tag{2}$$

where $J(x)$ is a Jacobian matrix. The Hessian matrix can be approximately expressed as $\Delta^2 F(x) \cong 2J^T(X)J(X)$. By the Gauss–Newton algorithm $X_{k+1} = X_k - [J^T(X_k)J(X_k)]^{-1} J^T(X_k)V(X_k)$, without calculating the second derivative, we can get the Levenberg–Marquardt algorithm:

$$\Delta X_k = -[J^T(X_k)J(X_k) + \mu_k I]^{-1} J^T(X_k)V(X_k) \tag{3}$$

Training is similar to the gradient descent algorithm in terms of learning speed when the parameter $\mu_k$increases, but moves closer to the Gauss–Newton algorithm when μ_k reduces to zero. In terms of learning speed, when the parameter increases, the training is similar to the gradient descent algorithm, and when reduces to zero, it moves closer to the Gauss–Newton algorithm. In the first few steps of the gradient descent method, training is very fast. However, the objective function decreases more slowly as the gradient moves toward zero. The Gauss–Newton method can identify optimal search directions when it is close to the optimal value. The ANN model has self-training abilities. It finds the intrinsic connections between inputs and outputs and establishes a data recognition model by learning. Different neural network architectures are defined by different mathematical models, the most influential one among which is the MLP model, which has the ability to learn arbitrarily complex nonlinear mappings from training data and to implement complex nonlinear classification discriminant functions. From the perspective of pattern recognition, the MLP model can be regarded as a general nonlinear classifier design. ANN models have been widely used for clinical

decision support. After proper training, an ANN can select the network structure with the most desirable performance.

3.3 Dataset and preprocessing

Many PD datasets are available for researchers to focus on voice patterns. The dataset for this study is the Parkinson Speech Dataset (Sakar et al. 2013), which was generated by the Department of Neurology of the Cerrahpasa Faculty of Medicine at Istanbul University and is available in the UCI machine learning repository. The dataset contains multiple types of sound recordings of vowel, number, word, and short sentence, which is suitable for comparing single-type and multi-type classification performance, and evaluating the reliability of the proposed method.

This dataset consists of separate training and testing files. The training data were collected from 20 PD patients (6 females, 14 males) and 20 healthy individuals (10 females, 10 males). Multiple speech recordings were collected and stored for each subject. For all subjects, 26 voice samples were collected, namely sustained vowel sounds for "a", "o", and "u", numbers from 1 to 10, nine words, and four short sentences. The testing files were collected from 28 PD patients who suffered from PD for 0 to 13 years. The patients were asked to say only the sustained vowel sounds "a" and "o" three times.

The accuracy of decision-making is directly associated with the quantity and quality of source data. Therefore, data preprocessing is necessary for network training. Data collected from training file and testing file were processed into vowel group (288 cases), number group (400 cases), word group (360 cases), and short sentence group (160 cases). Figure 1 presents the composition and processing parameters of the PD dataset.

3.4 Feature selection

We followed Sakar et al.'s method (Sakar et al. 2013) for extracting a set of 26 linear and time-frequency features from each speech sample. The following features of the PD dataset were used in this study: Jitter (local), Jitter (local, absolute), Jitter (rap), Jitter (ppq5), Jitter (ddp), Shimmer (local), Shimmer (local, dB), Shimmer (apq3), Shimmer (apq5), Shimmer (apq11), Shimmer (dda), AC, NTH, HTN, median pitch, mean pitch, standard deviation, minimum pitch, maximum pitch, number of pulses, number of periods, mean period, standard deviation of period, fraction of locally unvoiced frames, number of voice breaks, and degree of voice breaks.

Additionally, the PD dataset includes a status column with labels of "Y" for PD patients and "N" for healthy individuals. To determine the predictive power of different features, the collections and distributions of categorical variables were firstly analyzed by performing a chi-squared test ($p < 0.05$). Table 1 lists the statistical values of the features of the PD dataset with their corresponding definitions.

4 Experiments and analysis

4.1 Experimental setting

Experimental studies are performed on 64-bit Windows 10. The computer has Intel(R) Core(TM) i5-6300U CPU 2.40GHz processor and 8.00 GB RAM. The ANN model is constructed using the ANN tool in the Statistica 12.5 software (StatSoft, Inc., Tulsa, Oklahoma, USA) with an MLP base network and back-propagation training algorithm.

Separating data into training and testing sets is an important part of evaluating models. For the proposed ANN model, most of the data are used for training, which is the main part of training networks for learning and updating

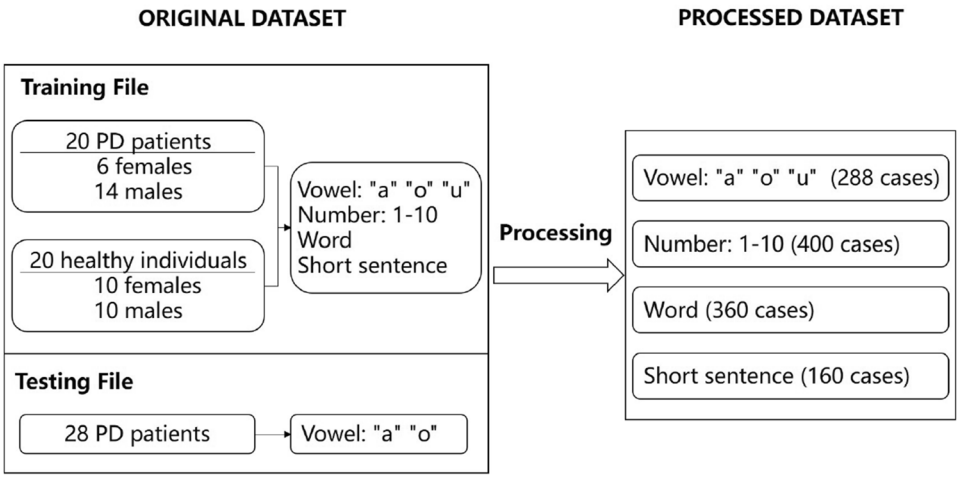

Fig. 1 Composition and processing of Parkinson original dataset

Table 1 Features extracted from voice samples and their statistical test for prognostic model

Group	Characteristic	Total n = 1208 (100%)	PD Yn = 688 (57%)	Healthy individual Nn = 520 (43%)	p-value
Frequency parameters	Jitter (local)	2.4 ± 1.81	2.31 ± 1.79	2.51 ± 1.83	0.062706
	Jitter (local, absolute)	0.0002 ± 0.0001	0.0002 ± 0.0001	0.0002 ± 0.0001	0.997054
	Jitter (rap)	1.12 ± 0.98	1.11 ± 0.94	1.14 ± 1.03	0.578218
	Jitter (ppq5)	1.21 ± 1.13	1.21 ± 1.04	1.22 ± 1.23	0.806954
	Jitter (ddp)	3.36 ± 2.93	3.32 ± 2.81	3.41 ± 3.08	0.578153
Amplitude parameters	Shimmer (local)	11.84 ± 5.84	11.06 ± 5.51	12.87 ± 6.11	0.000000
	Shimmer (local, dB)	1.09 ± 0.47	1.03 ± 0.47	1.18 ± 0.47	0.000000
	Shimmer (apq3)	5.28 ± 3.06	4.92 ± 2.66	5.75 ± 3.47	0.000003
	Shimmer (apq5)	7.3 ± 4.85	6.7 ± 3.78	8.09 ± 5.88	0.000001
	Shimmer (apq11)	11.1 ± 6.28	10.93 ± 6.77	11.34 ± 5.56	0.261488
	Shimmer (dda)	15.84 ± 9.18	14.76 ± 7.98	17.26 ± 10.4	0.000003
Harmonicity parameters	AC	0.86 ± 0.09	0.88 ± 0.08	0.84 ± 0.1	0.000000
	NTH	0.21 ± 0.16	0.18 ± 0.14	0.24 ± 0.17	0.000000
	HTN	11.3 ± 5.53	12.41 ± 5.87	9.83 ± 4.65	0.000000
Pitch parameters	Median pitch	163.54 ± 54.78	160.11 ± 46.8	168.08 ± 63.59	0.012190
	Mean pitch	168.06 ± 54.74	163.19 ± 48.15	174.5 ± 61.86	0.000366
	Standard deviation	24.41 ± 35.01	18.69 ± 31.03	31.99 ± 38.4	0.000000
	Minimum pitch	136.91 ± 47.72	136.59 ± 45.31	137.32 ± 50.77	0.794183
	Maximum pitch	226.33 ± 116.19	207.06 ± 99.95	251.81 ± 130.51	0.000000
Pulse parameters	Number of pulses	116.4 ± 141.27	126.08 ± 157.92	103.59 ± 114.5	0.006098
	Number of periods	112.91 ± 140.81	123.47 ± 157.86	98.93 ± 113.04	0.002674
	Mean period	0.0066 ± 0.0019	0.0067 ± 0.0019	0.0064 ± 0.0019	0.007284
	Standard deviation of period	0.0008 ± 0.0007	0.0007 ± 0.0007	0.0009 ± 0.0007	0.000000
Voicing parameters	Fraction of locally unvoiced frames	23.94 ± 21.59	19.18 ± 20.82	30.24 ± 20.99	0.000000
	Number of voice breaks	1.01 ± 1.56	0.82 ± 1.39	1.26 ± 1.74	0.000001
	Degree of voice breaks	10.74 ± 14.66	8.07 ± 12.73	14.28 ± 16.23	0.000000

The p-value is obtained by Chi-square test

n number, *Yn* number of PD patients, *Nn* number of healthy individual

*p < 0.05, significant input variables

weights, and a smaller portion of the data are used for testing. Backward-error propagation is used to implement the adaptive feedback required to adjust the weights during training. The errors of the initial classification recorded in the first are fed back into the network, and used to modify the network's algorithm the second time around, and so on for the next iterations repeatedly, causing the system to adjust the weights. Through various comparison experiments, we determine that 70% of the data are randomly assigned to the corresponding training groups for training the model, and the remaining 30% are assigned to the corresponding testing (validation) groups for testing the constructed models. Specifically, the training data are used for establishing and training ANN models, while the testing data are used to evaluate the predictive performance of the trained models.

The performance of the proposed models is evaluated by accuracy, sensitivity, specificity and visualized using the area under the receiver operating characteristic curve (AUC). When the following equations are examined with representing true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \tag{4}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

Accuracy is the ratio of the correctly predicted PD to the whole data. Sensitivity and specificity are important evaluation metrics in the field of biomedical science. Sensitivity is the ratio between how many patients are correctly

identified as PD to how many patients are actually that class of patients. Specificity is the ratio between how many individuals are correctly classified as not belonging to PD to the number of total individuals who are actually not PD. If the validation test reveals a high AUC, overall predictive accuracy, sensitivity, and specificity, it can be confirmed that a model can predict samples accurately without additional training. Our proposed ANN model is then compared with state-of-the-art models to determine if it has a better predictive performance.

4.2 Results and discussion

4.2.1 ANN model for PD prediction

The designed ANN model consists of three layers: input layer, hidden layer, and output layer. Figure 2 presents the structure of the final ANN model in this study.

The input layer contains 26 input parameters based on the features of the data discussed above. Two parameters are used in the output layer to give prediction results. Biases are added to the network at the hidden layer, and the number of parameters in the hidden layer is set empirically. The network has a feed-forward phase where the data is fed from the input towards the output and a back-propagation phase where the signals are sent back in a reverse direction to minimize the error. The processing unit in the output layer receives input values from the hidden layer to predict outputs. The information flow from the input layer to the output layer is formulated as follows:

$$y_k = \sum_{j=1}^{n_2} \omega_{ki} \cdot f\left(\sum_{i=1}^{n_1} \omega_{ij} x_i + b_i \right) \tag{7}$$

where x_i, ω_{ij}, b_i, y_k represent the input, weights, biases, and predicted value, respectively, and $f(x)$ is the activation function in the hidden layer.

The network adopts the learning rules of the gradient descent method. Its core is to backpropagate the error between the target output of the input layer and the calculation value of the output layer from the output to the input layer by layer and assign it to each connection point. The calculated reference errors of connection points are used to adjust the thresholds and weights of the network, which benefit the expected output of the network approximating to the actual output. The total cost value of the objective function can be denoted as follows:

$$E = \frac{1}{2} \sum_{j=1}^{N} \sum_{i=1}^{P} \left(d_i - y_i \right)^2 \tag{8}$$

where N, P, d_i, y_i represent the number of samples, nodes of the output layer, expected output, and actual output, respectively.

4.2.2 Comparative experiments on different pronunciation types for vocal tests

In this experiment, we establish four single-type of ANN models for vowel, number, word, and short sentence, denoted as model 1, model 2, model 3, and model 4, respectively.

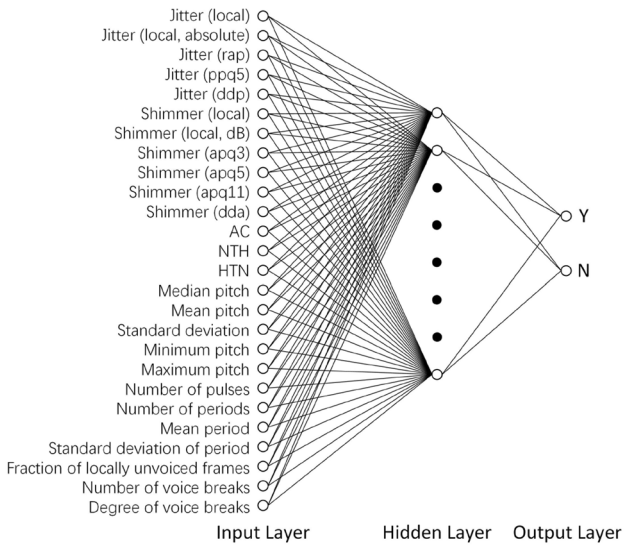

Fig. 2 ANN model for PD prediction

Table 2 Training data and validation test data of ANN models 1–4

Model	Total N	Training (%)	TN	Testing (%)	VN
Model 1	288	70	202	30	86
Model 2	400	70	280	30	120
Model 3	360	70	252	30	108
Model 4	160	70	112	30	48

N number, *TN* number of training data, *VN* number of testing data

Table 3 The performance comparison of ANN models 1–4

Name	ANN model	Acc (%)	Sen (%)	Spe (%)	AUC (%)
Model 1	MLP 26-5-2	91	99	82	91
Model 2	MLP 26-8-2	83	84	84	90
Model 3	MLP 26-5-2	81	88	81	90
Model 4	MLP 26-4-2	75	69	76	78

Acc accuracy, *Sen* sensitivity, *Spe* specificity, *AUC* area under the receiver operating characteristic curve

For each model, 70% of the corresponding data are randomly assigned to a training group (202 cases for the vowel group, 280 cases for the number group, 252 cases for the word group, and 112 cases for the short sentence group), and the remaining 30% are assigned to a testing group (86 cases for the vowel group, 120 cases for the number group, 108 cases for the word group, and 48 cases for the short sentence group) for constructing models for validation. Table 2 lists the details of four groups.

The validity of the models is measured in terms of accuracy, sensitivity, specificity, and AUC. The simulation results for the selected models are reported in Table 3. For the vowel dataset, MLP 26-5-2 (model 1) exhibits a testing accuracy of 91%, sensitivity of 99%, specificity of 82%, and AUC of 91%. For the number dataset, MLP 26-8-2 (model 2) exhibits a testing accuracy of 83%, sensitivity of 84%, specificity of 84%, and AUC of 90%. For the word dataset, MLP 26-5-2 (model 3) exhibits a testing accuracy of 81%, sensitivity of 88%, specificity of 81%, and AUC of 90%. For the short sentence dataset, MLP 26-4-2 (model 4) exhibits a testing accuracy of 75%, sensitivity of 69%, specificity of 76%, and AUC of 78%. One can see that, according to the results (Table 3), the ANN constructed with single-type vowel dataset exhibits the highest recognition rate, followed by the ANNs constructed from the number dataset and word dataset. The ANN model with short sentence dataset is the one with the lowest performance.

The receiver operating characteristic (ROC) curve is a graphical plot that illustrates the predictive ability of a binary classifier system with varying discrimination thresholds. A ROC curve is generated by plotting the true positive rate against the false positive rate at various threshold settings. By comparing the ROC curves in Fig. 3, one can see that model 1 is superior to other models because at all cut-offs the true positive rate is higher and the false positive rate is lower for model 2, model 3, and model 4. The area under the curve of model 1 is larger than that of the other models. The ROC curve reflects a model's ability to recognize diseases at any threshold. It means that model 1 provides the most accurate recognition and has the largest AUC, indicating that the overall performance of model 1 is better than those of models 2, 3, and 4. It can be concluded that the proposed ANN model using single-type vowel as speech inputs has greater predictive power than the models using number, word, and short sentence as inputs. It indicates that single-type vowel pronunciation is more helpful for constructing stable models and more efficient in predicting PD compared to other types of pronunciations.

Table 4 Training data and validation test data of ANN models 5–8

Model	Total N	Training (%)	TN	Testing (%)	VN
Model 5	288	70	202	30	86
Model 6	688	70	482	30	206
Model 7	1048	70	734	30	314
Model 8	1208	70	846	30	362

N number, *TN* number of training data, *VN* number of testing data

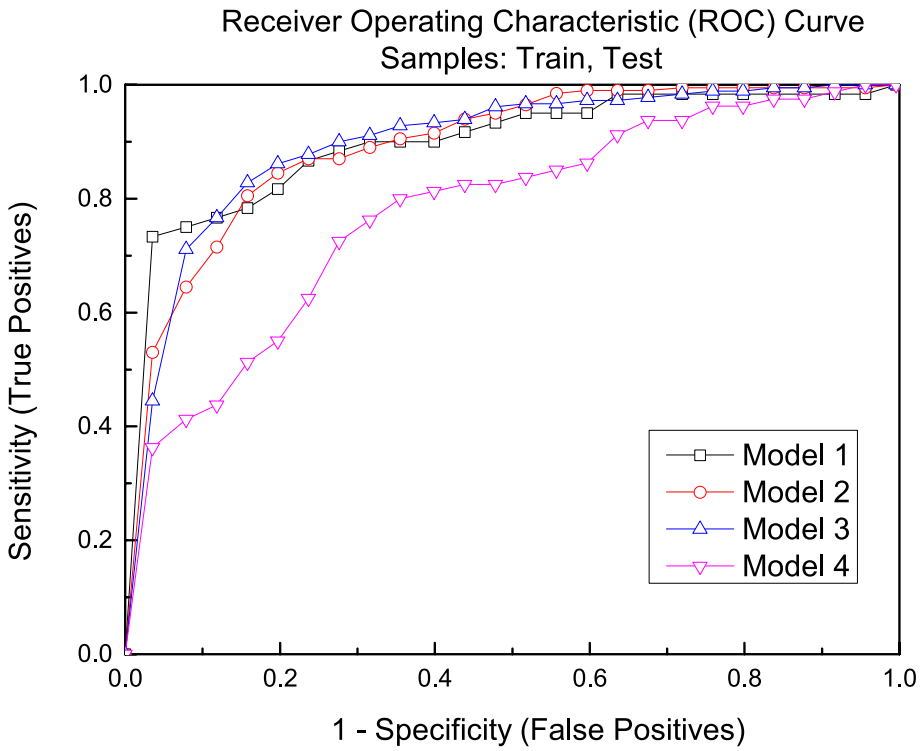

Fig. 3 Comparison of the models 1–4 in terms of their ROC curves

Table 5 Performance comparisons between ANN models 5–8

Names	ANN Model	Acc (%)	Sen (%)	Spe (%)	AUC (%)
Model 5	MLP 26-5-2	91	99	82	91
Model 6	MLP 26-10-2	80	93	69	90
Model 7	MLP 26-11-2	75	87	66	85
Model 8	MLP 26-8-2	75	87	71	87

Acc accuracy, *Sen* sensitivity, *Spe* specificity, *AUC* area under the receiver operating characteristic curve

For evaluation, four additional models (Models 5-8) are constructed with single-type speech samples versus combinations of multi-type speech samples. Model 5 uses the vowel dataset alone, model 6 uses the vowel and number datasets, model 7 uses the vowel, number, and word datasets, and model 8 uses all four datasets. Table 4 summarizes the characteristics of models 5 to 8.

For each, 70% of the corresponding data are used for training and the remaining 30% are used for testing. The validity of the models is measured in terms of accuracy, sensitivity, specificity, and AUC. The simulation results for the selected models are reported in Table 5. MLP 26-5-2 (model 5) exhibits a testing accuracy of 91%, sensitivity of 99%, specificity of 82%, and AUC of 91%. MLP 26-10-2 (model 6) exhibits a testing accuracy of 80%, sensitivity of 93%, specificity of 69%, and AUC of 90%. MLP 26-11-2 (model 7) exhibits a testing accuracy of 75%, sensitivity of 87%, specificity of 66%, and AUC of 85%. MLP 26-8-2 (model 8) exhibits a testing accuracy of 75%, sensitivity of 87%, specificity of 71%, and AUC of 87%. From the results in Table 5, it can be concluded that model 5 has the best performance out of the four models, followed by models 6 and 7, while model 8 is the one with the lowest performance.

Finally, performance in terms of AUC and predictive accuracy are evaluated and analyzed. By comparing the ROC curves in Fig. 4, one can see that for the single-type vowel dataset, model 5 generates the ROC curve closest to the upper-left corner, representing that it had the most accurate results and largest AUC. The area under the curve for model 5 is larger than the area under the curve of other models. The performance of model 5 is superior to those of model 6, 7, and 8, because at all cut-offs the true positive rate is higher and the false positive rate is lower than other models, which means the single-type vowel-based model provides better accuracy than models with multi-type samples combined vowel, number, word, and short sentence. When the number of pronunciation types increases, the prediction accuracy decreases. The more pronunciation types, the lower the prediction accuracy.

4.2.3 Vowel-based ANN model for PD prediction

Following the approach of the studies above, in this experiment, we select the best performing model (MLP 26-5-2)

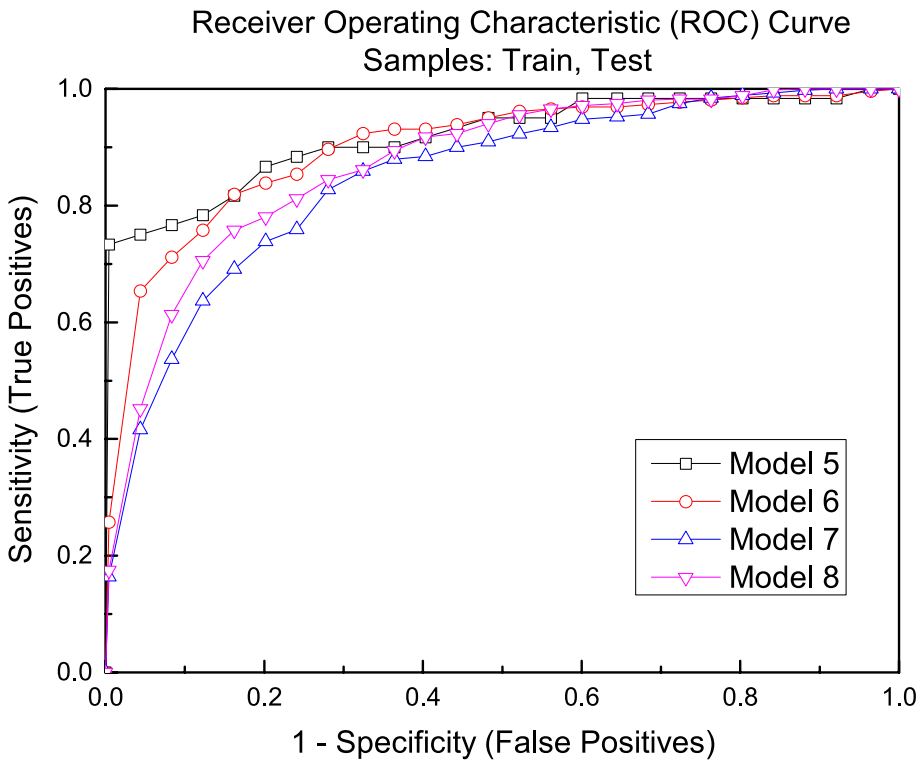

Fig. 4 Comparison of the models 5–8 in terms of their ROC curves

Table 6 Vowel input variables features and their statistical test for prognostic model

Group	Characteristic	Total n = 1208 (100%)	PD Yn = 688 (57%)	Healthy individual Nn = 520 (43%)	p-value
Frequency parameters	Jitter (local)	0.72 ± 0.78	0.69 ± 0.79	0.82 ± 0.73	0.262016
	Jitter (local, absolute)	0 ± 0.0001	0 ± 0.0001	0.0001 ± 0.00005	0.396993
	Jitter (rap)	0.38 ± 0.44	0.37 ± 0.44	0.42 ± 0.44	0.423553
	Jitter (ppq5)	0.4 ± 0.47	0.4 ± 0.49	0.4 ± 0.36	0.921438
	Jitter (ddp)	1.13 ± 1.33	1.1 ± 1.33	1.26 ± 1.32	0.423552
Amplitude parameters	Shimmer (local)	6.2 ± 4.21	5.79 ± 3.48	7.76 ± 6.02	0.001150
	Shimmer (local, dB)	0.57 ± 0.36	0.54 ± 0.31	0.71 ± 0.5	0.000990
	Shimmer (apq3)	3.17 ± 2.35	2.95 ± 1.95	4 ± 3.36	0.002084
	Shimmer (apq5)	3.76 ± 2.83	3.44 ± 2.06	4.95 ± 4.58	0.000215
	Shimmer (apq11)	5.05 ± 3.04	4.84 ± 2.75	5.84 ± 3.9	0.023574
	Shimmer (dda)	9.51 ± 7.04	8.86 ± 5.85	11.99 ± 10.09	0.002084
Harmonicity parameters	AC	0.95 ± 0.06	0.96 ± 0.05	0.93 ± 0.09	0.002030
	NTH	0.06 ± 0.1	0.05 ± 0.08	0.1 ± 0.16	0.001561
	HTN	18.29 ± 5.69	18.59 ± 5.55	17.14 ± 6.1	0.077753
Pitch parameters	Median pitch	166.78 ± 46.99	165.62 ± 46.21	171.18 ± 49.97	0.415437
	Mean pitch	167.08 ± 47.15	165.23 ± 46.1	174.08 ± 50.73	0.196448
	Standard deviation	7.61 ± 13.46	5.73 ± 7.66	14.76 ± 24.28	0.000003
	Minimum pitch	150.94 ± 48.51	151.22 ± 48.23	149.88 ± 49.96	0.849369
	Maximum pitch	187.83 ± 70.07	177.82 ± 53.88	225.84 ± 104.19	0.000002
Pulse parameters	Number of pulses	243.97 ± 228.61	225.86 ± 233.63	312.78 ± 195.27	0.008546
	Number of periods	241.92 ± 228.41	224.18 ± 233.55	309.32 ± 195.12	0.009962
	Mean period	0.0065 ± 0.0019	0.007 ± 0.002	0.0062 ± 0.0017	0.232588
	Standard deviation of period	0.0003 ± 0.0004	0.0003 ± 0.0003	0.0004 ± 0.0005	0.000271
Voicing parameters	Fraction of locally unvoiced frames	1.62 ± 4.23	0.95 ± 2.74	4.17 ± 7.04	0.000000
	Number of voice breaks	0.27 ± 0.91	0.23 ± 0.85	0.45 ± 1.11	0.092615
	Degree of voice breaks	0.85 ± 3.27	0.63 ± 2.58	1.7 ± 5.04	0.023315

The p-value is obtained by Chi-square test

n number, *Yn* number of PD patients, *Nn* number of healthy individual

*p < 0.05, significant input variables

Table 7 The performance of the ANN model for vowel dataset

Name	Acc	Sen	Spe	Pre	F1	AUC
MLP 26-5-2	91%	99%	82%	96%	98%	91%

Acc accuracy, *Sen* sensitivity, *Spe* specificity, *Pre* precision, *F1* F1-score, *AUC* area under the receiver operating characteristic curve

as the final proposed model for evaluation. Only the single-type vowel voice samples from different subjects are considered. The input variables for the vowel dataset are analyzed according to p-values. The vowel input variable group used for this validation study is presented in Table 6. The results demonstrate that there are no significant differences among most variables.

As can be seen from Table 7, a PD ANN model with 26 features, MLP 26-5-2 exhibits an accuracy of 91%, sensitivity of 99%, specificity of 82%, precision of 96%, F1-score of 98%, and AUC of 91% on the testing set.

Figure 5 presents a ROC curve with an AUC of 91%. The larger the AUC, the greater the prediction accuracy. On the ROC curve, the point closest to the upper-left of the graph represents a critical value with high sensitivity and specificity. From Fig. 5, one can see that the model has high prediction accuracy.

Cumulative gain and lift chart is also an excellent tool for visualizing the performance of the model. Figure 6 presents a cumulative gain and lift chart with a baseline. A cumulative gain and lift chart compares the predictive performance of a target model to that of a random model. The greater the area between the lift curve and baseline

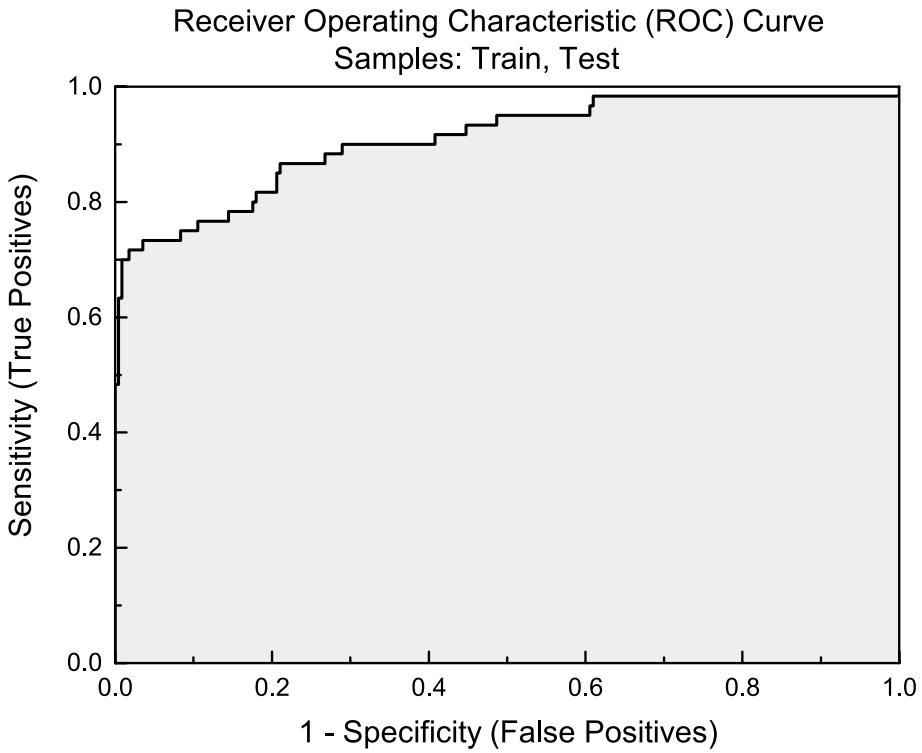

Fig. 5 The ROC curve of the ANN model for vowel dataset

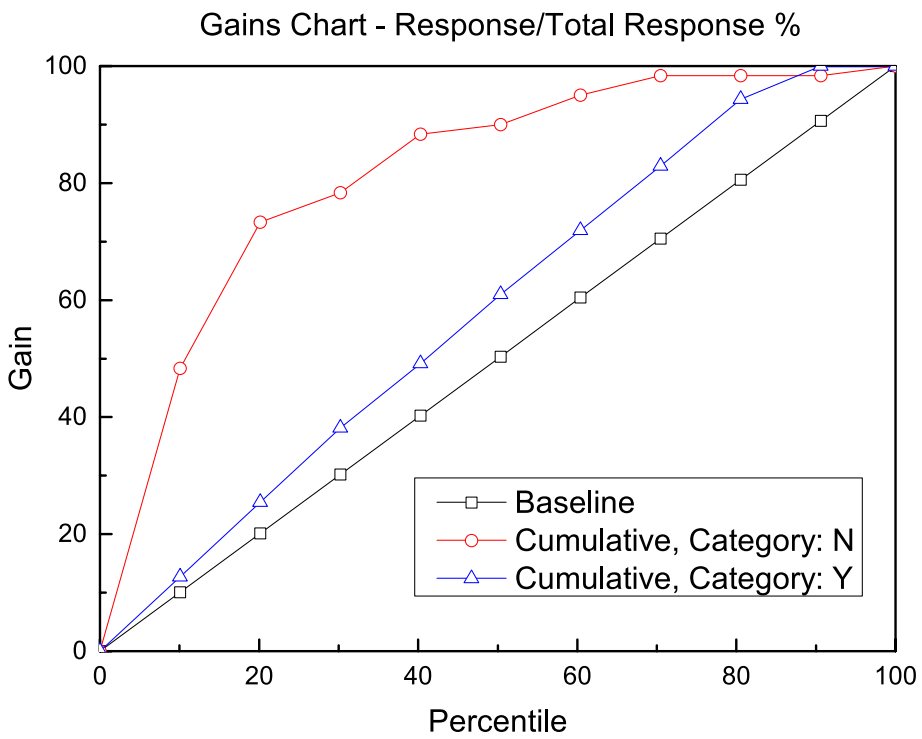

Fig. 6 The cumulative gains chart with baseline of the ANN model for vowel dataset

(random), the greater the model performance. Figure 6 indicates that the proposed model achieves excellent performance.

We then compare the performance of our method with other methods reported for PD detection problems based on multiple types of voice recordings data. The comparative study is performed from two aspects i.e., PD detection

Table 8 Comparative study of the proposed method with other methods

Study	Method	Acc	Sen	Spe
Sakar et al. (2013)	K-NN + SVM (linear kernel best)	85%	80%	90%
	K-NN + SVM (RBF kernel best)	80%	85%	75%
Behroozi and Sami (2016)	Multiple classifier framework	88%	90%	85%
Li et al. (2017)	Hybrid feature learning + SVM	83%	85%	80%
Benba et al. (2017)	HFCC + SVM	88%	90%	85%
Ali et al. (2019)	LDA + ANN + GA	82%	–	–
Gunduz (2019)	9-layered CNN + SVM	87%	–	–
Soumaya et al. (2020)	SVM + GA (15 features) MFCC+MLP (20 features) SVM (20 features)	91% 80% 73%	-	-
Proposed method	ANN + vowel	91%	99%	82%

Acc accuracy, *Sen* sensitivity, *Spe* specificity

accuracy and generalization capabilities. The literature survey shows that the proposed approach achieve better results than all the previous methods to the best of our knowledge. A brief description of these methods and their achieved accuracies are reported in Table 8.

4.3 Discussion

The reliability and accuracy of the clinical prediction of PD is still limited, especially in the early stages. To solve this problem, we develop a realistic and effective ANN model with the simplest pronunciation for discriminating PD patients from healthy individuals and maximize the accuracy of our proposed method.

Firstly, a novel multi-layer neural network model based on features of human speech is proposed to improve the quality of early PD prediction in this study. When choosing an algorithm, the following factors should be taken into account: the accuracy of the model, the generalization capabilities, feasibility of deployment, the available data, and the time taken to train the model. This is not only a practical issue of making model deployment more stable but also an important issue of how to make the model learn the mechanics of the data. There is no advantage in accuracy to use SVM compared to an ANN classifier, and CNN is not suitable for practical deployment because of its black-box nature. Compared with these widely used algorithms, ANN is the most suitable for PD prediction. Our ANN model is a three-layered feed forward model consisting of an input layer, a hidden layer, and an output layer (Fig. 2).

Secondly, using single-type vowel pronunciations can help to establish a universally applicable PD early predictive model for different speech systems. Pronunciation differences among regions and cultures should be taken into consideration. In contrast to multiple types of samples, we believe that a single-type of pronunciation may perform better. We've defined some sets of comparative experiments. Experimental results from (Table 3, Fig. 3) demonstrate that the model using vowel as speech inputs has greater predictive power than the models using number, word, and short sentence. This finding indicates that vowel pronunciation is more helpful for constructing stable models. This may be because vowel pronunciations are simpler and less noisy, and can minimize the difference between the pronunciation of individual pronunciations and cross-regional languages. Experimental results (Table 5, Fig. 4) demonstrate that a single-type vowel-based model provides better accuracy than multi-type models that combined vowel, number, word, and short sentence. Additionally, the prediction accuracy is reduced when the number of pronunciation types increases. The possible cause is the effect of fine-tuning. The more complex a pronunciation, the more complicated the time-frequency features in corresponding speech samples. It is very difficult to speak without an accent, but differences in vowel pronunciations are relatively small.

Finally, experimental results (Table 7, Figs. 5, 6) indicate that the proposed model achieves excellent performance. Experimental results (Table 8) show that the proposed method outperforms the state-of-the-art methods in terms of PD prediction accuracy on voice data. Therefore, according to the experiments above, it can be concluded that our proposed vowel-based ANN model based on single-type phonation for predicting PD has significant predictive power.

However, the predictive power of the proposed evaluation model may be lower in real world applications compared to that in an ideal test environment. This is because the verification data in real world applications may contain more complex characteristics and noise compared to pristine training sets.

5 Conclusions

Early PD prediction and treatment can help PD patients manage their symptoms and maintain their quality of life. In this paper, we propose a vowel-based ANN model based

on single vowel phonation for predicting PD. Experimental results show that our proposed multi-layer neural network based on speech features is more efficient, stable, and robust than other advanced machine learning methods such as SVM and CNN, and vowel pronunciations are more suitable for applying a unique classifier instead of multiple types of pronunciations. The proposed method achieves a prediction accuracy of 91%, sensitivity of 99%, specificity of 82%, and AUC of 91%, which is superior to the performance of previous methods. It can be concluded that our proposed model has the potential to help physicians improve the quality of decision-making during the prediction process of PD patients, particularly for those in the early stages. Regarding future work, we aim to extend our recent research to other languages.

Acknowledgements This work was supported in part by the National Natural Science Foundation of China under Grant 61802076 and 61632009, in part by the Guangdong Provincial Natural Science Foundation under Grant 2017A030308006, in part by the High-Level Talents Program of Higher Education in Guangdong Province under Grant 2016ZJ01, and in part by Hainan Provincial Natural Science Foundation of China under Grant number 619MS057.

Declarations

Human participants or animals This article does not contain any studies with human participants or animals performed by any of the authors. In this experiment, we did not collect any samples of human and animals.

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