Parkinson's Disease Recognition through Vertical Ground Reaction Force via WOA-SVM

Fenggang Liu and Huiquan Chen

Abstract—**Parkinson's disease (PD) is one of the most critical neurological diseases, which would lead to the abnormality of human motion and reduction of life quality. The changes in the PD patients' motion are the most obvious clinical signs, which attracts many researchers' interest to diagnose the PD patients. In an effort to efficiently differentiate the PD patients from the healthy persons, the support vector machine (SVM) model is selected. Additionally, to solve the problem of low accuracy induced by improper parameters of SVM model, the improved whale optimization algorithm (IWOA) is selected to optimize the parameters in the kernel function of SVM. The IWOA integrates four key mechanisms, including in Lévy flight strategy, nonlinear convergence factors, adaptive weighting, and reflective boundary handling. The public PD dataset is segmented into the training data and testing data. Specifically, the training data are input into the IWOA-SVM model to gain the best parameters, while the testing ones are used to predict the PD patients from the healthy persons through the SVM model with the optimal parameters. Finally, three evaluation metrics are selected to evaluate the results, such as accuracy, sensitivity and specificity. The recognition results of the presented method are compared with the other three methods. The experimental results show that the IWOA-SVM algorithm achieves the best performance in PD detection.**

Index Terms—**Parkinson's disease; SVM; IWOA; Lévy flight strategy.**

I. INTRODUCTION

Parkinson's disease (PD) can influence the older people's motion, and be distinguished by the loss of resting tremors, dopamine neurons and slowness of movement [1]. This disease would cause the primary motor defects of tremor and gait disturbances [2-3]. The assessment of PD depends on the sufferers' clinical presentation and the clinician's expertise. However, the complexity of PD can lead to variability in assessment and misdiagnosis [4]. Thus, an effective decision support method should be provided for clinicians to make accurate diagnoses.

Gait disturbances is one of the most common features for PD, and gait analysis could help identify the healthy persons from the PD patients [5]. To be specific, the kinematic features from different gait patterns can assist to detect the PD and assess the seriousness level, which is less influenced by the physiological parameters, including gender, weight, age and height. Many researches reported the PD diagnosis based on gait analysis through the substantial computational methods like the wavelet decomposition [6], deterministic learning theory [7] and convolutional neural network [8]. However, the exploring of optimal kinematic features for PD prognosis have not reached its full potential [9-11]. Govindu and Palwe analysed the performance of four classifiers like support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF) and logistic regression to distinguish the healthy persons and PD sufferers through the audio dataset [12]. This approach achieved a maximum detection accuracy and sensitivity by the RF. Ogul et al. combined the artificial neural networks and local binary pattern to get a high accuracy of 98.3% and high correlation coefficient of 0.959 in PD detection [13]. Tao Zhang et al. utilized the energy direction based on empirical mode decomposition, which achieved the average accuracies of 96.54% and 92.59% on the voice datasets [14]. Lee and Lim presented a method to distinguish the PD sufferers and healthy persons through the gait features and wavelet-based feature extraction [15]. Forty features are extracted through the methods of frequency distributions and variabilities. Balaji et al. utilized the long short term memory network (LSTM) method for PD diagnosis through gait patterns [16]. Three gait datasets are selected for training the LSTM network. The experimental results demonstrated that the LSTM algorithm provided high accuracies of 98.6% and 96.6% for binary and multi-class classification, respectively.

The SVM algorithm can solve the problems of regression and linear/nonlinear classification, and be selected to realize the PD detection. The core of SVM is to find a hyperplane to differentiate two types of data with unique labels. Benba et al adopted the SVM model to identify the PD patients with voice disorders [17]. The features were extracted through the frequency coefficients, and the experiments showed that the presented method achieved a high accuracy of 91.17%. Soumaya et al combined the SVM model with the genetic algorithm (GA) to recognize the PD patients through the speech signals [18]. The best accuracy of combining the GA and SVM was 91.18%. Jin et al. utilized the SVM to classify the PD based on the diffusion magnetic resonance imaging data. The results were analyzed through five regions that the SVM obtained a high accuracy of 81.25%.

The whale optimization algorithm (WOA) method can realize the parameter optimization with exploitation capacity and adaptive exploration. Many studies have been made to optimize the model through WOA [20]. Zhou et al. presented an enhanced WOA method to search the best parameters for the engineering applications [21]. Liang et al. used the WOA to optimize the neural network to solve the problem of wastewater treatment [22]. Yu et al. introduced the WOA to optimize the hyper parameters of LSTM to predict the intrinsic mode function for a reliable forecast of photovoltaic power [23]. The results showed that the presented method

Manuscript received March 27, 2025; revised August 16, 2025.

Fenggang Liu is an Associate Professor at the School of Artificial Intelligence, Wuchang University of Technology, Wuhan, 430221, China. (corresponding author to provide phone: +86 15377677072; e-mail: fg_liu1314@163.com).

Huiquan Chen is an Engineer of China Mobile System Integration Co.,Ltd, Xian, China. (e-mail: chenhuiquan@cmict.chinamobile.com).

can realize more reliable prediction interval.

However, more studies about WOA had been published to optimize the parameters for SVM model. Kose used the WOA to optimize the sigma parameter in the Gaussian kernel function of SVM model for fault diagnosis [24]. Samantaray utilized the WOA-SVM model to predict the suspended sediment concentration in Mahanadi river [25]. Sahoo and Ghose applied the WOA-SVM model to forecast the stream flow of Barak river, and gained reliable results [26]. Kong employed the WOA-SVM model to accurately estimate the tool wear in titanium alloy [27]. The WOA was used to optimize the parameters in kernel function of SVM, and this method was tested on two different databases, and severally gained high accuracies of 97.89% and 99.27%.

In this paper, the PD classification is completed through the SVM model whose parameters in kernel function are searched though the whale optimization algorithm (WOA) algorithm. Through collecting the data from sixteen pressure sensors and kinematic analysis, thirty features are extracted and substituted into the SVM model. Searching the optimal parameters in kernel function of SVM would benefit better identification result. The improved WOA (IWOA) algorithm is utilized to find the optimal parameters in kernel function, and the best parameters are updated for SVM model. Finally, in order to solve the problem of over-fitting, the ten-fold cross validation method is selected. The performance of the IWOA-SVM model is assessed, and the efficacy is evaluated through the three key performance metrics, such as precision, sensitivity and specificity.

II. Materials and Method

A. Dataset description

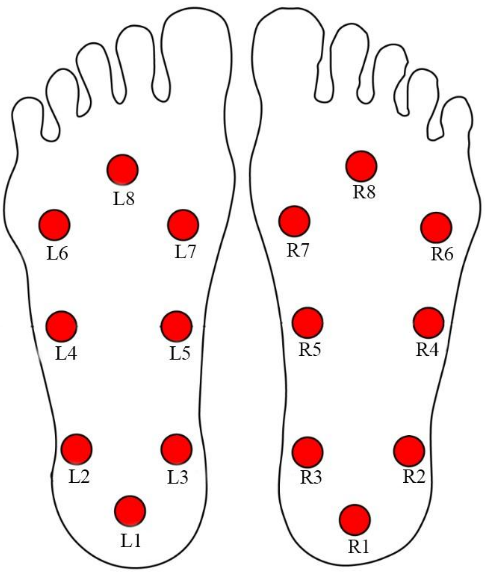
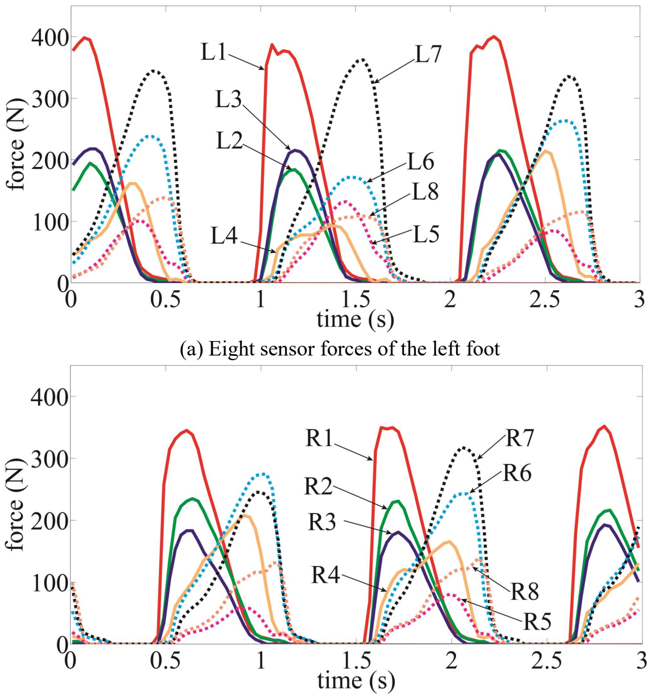


Fig.1. Positions of FSRs in the sole of foot.

The dataset in this research is derived from the open dataset "Gait in Parkinson's Disease" published in the complex physiological signals research resource network (PhysioNet). The dataset consists of 306 records from three research groups, including 214 PD patients and 92 healthy persons, as listed in Table I. Each record of the dataset consists of sixteen vertical ground reaction forces which are measured by force sensors. These force sensors are placed in the shoe sole, and their distribution is shown in Fig. 1.

Table I
Demographic details of three groups

Groups	Types	Numbers
Ga	Healthy	38
	PD patient	75
Ju	Healthy	25
	PD patient	104
Si	Healthy	29
	PD patient	35



(a) Eight sensor forces of the left foot

(b) Eight sensor forces of the right foot

Fig.2. FSRs sensor data of eight FSRs: (a) the left foot, (b) the right foot.

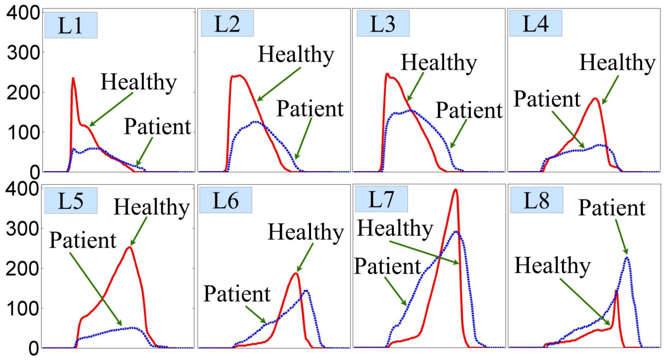


Fig. 3. Difference between the healthy person and PD patient.

Fig.2(a) and (b) show the pressures of eight FSRs from the left and right foot, respectively. Fig. 3 depicts the difference between the healthy person and the PD patient. Firstly, it can be highlighted that the pressures from the PD patient are significantly smaller than that from the healthy person. Secondly, the moments of their initial contact (IC) and the peak occurring were different. These features can be used to differentiate them.

B. Evaluation Manners

The confusion matrix (CM) is selected to evaluate the performance of classifying PD patients from the healthy persons. Specifically, a CM includes four predicted classes, such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN). To quantify the results efficiently, three performance metrics are considered, including sensitivity (Sen), accuracy (Acc) and specificity (Spe). The three performance metrics are listed in Table II.

TABLE II
PERFORMANCE METRICS FOR CLASSIFIER

Parameter	Expression
Sensitivity	$Sen(\%)=\frac{TP}{TP+FN}\times100\%$
Accuracy	$Acc(\%)=\frac{TP+TN}{TP+FP+FN+TN}\times100\%$
Specificity	$Spe(\%)=\frac{TN}{TN+FP}\times100\%$

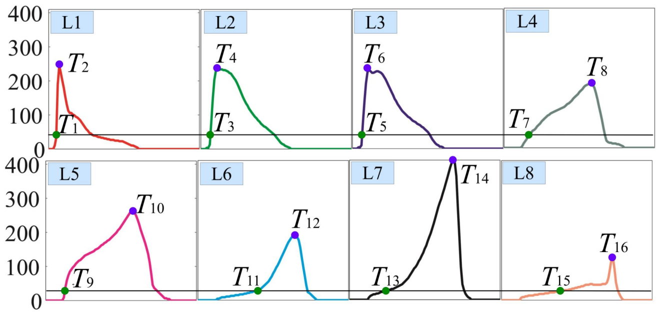


Fig. 4. Marked moments of IC and peak occurring.

TABLE III
FEATURES DESCRIPTION

Feature	Symbol	Description
Step time 1	$\Delta t_1=T_2-T_1$	Time between IC of the first point to the peak of the 1st point
Step time 2	$\Delta t_2=T_3-T_1$	Time between IC of the first point to IC of the 2nd point
Step time 3	$\Delta t_3=T_4-T_1$	Time between IC of the first point to the peak of the 2nd point
Step time 4	$\Delta t_4=T_5-T_1$	Time between IC of the first point to IC of the 3rd point
Step time 5	$\Delta t_5=T_6-T_1$	Time between IC of the first point to the peak of the 3rd point
Step time 6	$\Delta t_6=T_7-T_1$	Time between IC of the first point to IC of the 4th point
Step time 7	$\Delta t_7=T_8-T_1$	Time between IC of the first point to the peak of the 4th point
Step time 8	$\Delta t_8=T_9-T_1$	Time between IC of the first point to IC of the 5th point
Step time 9	$\Delta t_9=T_{10}-T_1$	Time between IC of the first point to the peak of the 5th point
Step time 10	$\Delta t_{10}=T_{11}-T_1$	Time between IC of the first point to IC of the 6th point
Step time 11	$\Delta t_{11}=T_{12}-T_1$	Time between IC of the first point to the peak of the 6th point
Step time 12	$\Delta t_{12}=T_{13}-T_1$	Time between IC of the first point to IC of the 7th point
Step time 13	$\Delta t_{13}=T_{14}-T_1$	Time between IC of the first point to the peak of the 7th point
Step time 14	$\Delta t_{14}=T_{15}-T_1$	Time between IC of the first point to IC of the 8th point
Step time 15	$\Delta t_{15}=T_{16}-T_1$	Time between IC of the first point to the peak of the 8th point

C. Feature Extraction

In Reference [5], the same datasets were used to extract the gait spatiotemporal features, such as stride time, step time, swing time, stride length and step length. These features were input into the SVM model in order to distinguish the PD patients from healthy ones. In this paper, we select different features to realize this goal. As pictured in Figure 4, the moments of IC and peak occurring are marked for each pressure, and the extracted features are listed in Table III. For one foot, fifteen features are extracted, and thirty features will be acquired for one person. As one single walk has multiple cycles, the final features are obtained by averaging.

III. ALGORITHM DESIGN

The WOA can solve the engineering optimization issues with many advantages, such as quick convergence speed, simplicity and flexibility. Moreover, the WOA has a notable feature of balanced implementation. Specifically, the WOA can equally achieve the local search and global research for each parameter even with a smaller number of dataset. Due to its effectiveness and adaptability, we choose the WOA to find the best parameters in kernel function of support vector machine (SVM) model. Figure 5 described the presented PD classification through WOA optimizer and SVM classifier. The following part is a brief introduction of WOA and SVM related principles.

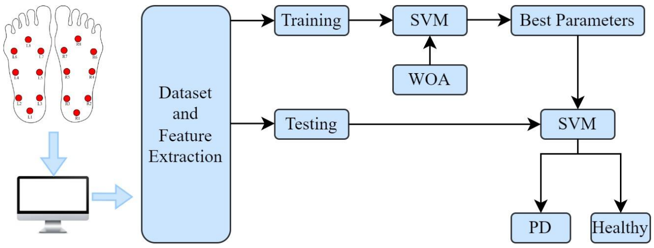


Fig. 5. Flow diagram of WOA optimizing SVM.

A. Support Vector Machine

The basic of SVM in classifying two data is to define a maximum margin in the feature space. The learning strategy of SVM is to minimize the hinge loss function, and solve the convex quadratic programming. The kernel techniques would make the SVM accomplish the non-linear classification. Therefore, the SVM algorithm can effectively predict gait types and identify gait results under different pressure data. Suppose that the linearly separable sample set is (x_i, y_i), i=1, 2, ..., n, $x\in R^d$ $y\in\{+1, -1\}$ defined as the class type. Normalize the discriminant function g(x)=$w\cdot x+b$ in d-dimensional space and satisfy the condition $|g(x)|>1$ for all samples in both categories. The equation is written as follows.

$$y_i[(w\cdot x_i)+b]-1\geq 0, i=1,2,\cdots,n \tag{1}$$

where x_i means the input and y_i is the output. The equation of classification line is $w\cdot x+b$=0, and classification interval equals $2/\|w\|$. It will fit the Equation (1) in the case that the interval is greatest when $\|w\|$ or $\|w\|^2$ is the smallest, and the optimal classification surface is the surface when $\frac{1}{2}\|w\|^2$ is smallest. Thus, the problem of optimal classification surface can be rewritten as the linear constrained optimization problem which is under the constraint of Equation (1). This condition can be expressed in the following.

$$\min J(w,e) = \frac{1}{2}\|w\|^2 + \frac{1}{2}C\sum_{i=1}^{n} e_i^2 \tag{2}$$

where e is the loss function, and C is the penalty factor. In order to solve nonlinear problems, SVM introduces Gaussian kernel function, and the formula is expressed as follows.

$$K(x,z) = \exp(-\gamma\|x-z\|^2) \tag{3}$$

Define the Lagrange function as follows:

$$L(w,b,a,e) = \frac{1}{2}\|w\|^2 + \frac{1}{2}C\sum_{i=1}^{n} e_i^2 - \frac{1}{2}\sum_{i=1}^{n} a_i\{y_i[w\cdot x_i + b] - 1\} \tag{4}$$

where a_i is the Lagrange coefficient. In order to search the minimum values for w and b of Lagrange function, the partial derivative of w and b is set be 0. Therefore, this can be described into the below dual problem.

$$\begin{cases} \sum_{i=1}^{n} a_i y_i = 0 \\ a_i \ge 0, i = 1,2,\cdots,n \\ Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j y_i y_j (x_i x_j) \end{cases} \tag{5}$$

On the basis of the Kuhn-Tucker condition, the method of solving this optimization problem could be written in the following.

$$f(x) = \operatorname{sgn}\{(w''\cdot x) + b''\} = \operatorname{sgn}\{\sum_{i=1}^{n} a_i''\cdot y_i(x_i\cdot x) + b''\} \tag{6}$$

where $\operatorname{sgn}(\cdot)$ means the sign function and b'' indicates the threshold for classification. Therefore, a_i'' are all 0 in solution which corresponds to Equation (6). And samples a_i'' with non-zero values are support vectors with only a small part of gait data samples. The optimal classification function obtained after solving the above problems is written as follows.

B. Whale Optimization Algorithm

The basic of WOA aims to mimic the hunting behavior of whales, while the hunting behavior is mainly divided into three steps such as encircling the prey, bubbling net attack, and hunting for food. The process of WOA can be regarded as several individual whales continuously updating their individual positions until an approving solution is found. Firstly, the sperm whale is able to recognize the prey location and surround it. However, since the optimal position is unknown in the search space, the WOA algorithm is assumed that the best solution is the target prey or closed to the optimal one. Once the optimal search agent is determined, the other agents would attempt to update their positions with respect to the best agent. This behavior can be expressed as the following equation.

$$X(t+1) = X_{best}(t) - A\cdot\left|C_a X_{best}(t) - X(t)\right| \tag{7}$$

where X is a position vector, and X_{best} is the best position vector. C_a and A are the coefficient vectors which can be defined as follows.

$$\begin{cases} A = 2ar_1 - a \\ C_a = 2r_2 \\ a = 2 - \frac{2t}{T} \end{cases} \tag{8}$$

where r_1 and r_2 are the random vectors within the range of [0,1]. t and T are the current and maximum iteration, respectively. As the iteration progresses, a linearly decreases from the maximum to zero. The humpback whale can also use spiral bubbles to capture the prey. This method computes the distance between the whale and the prey to establish a spiral equation in the following.

$$X(t+1) = \left|C_a X_{best}(t) - X(t)\right|\cdot e^{bl}\cos(2\pi l) + X_{best}(t) \tag{9}$$

where |*| means a operator to compute the distance, b indicates a constant, and l is a random value in the range of [-1,1] that is multiplied element-wise. Whales randomly choose between the bubble-netting and spiral-bubble methods for hunting, therefore we use 'prob' to make a random selection. The equation is written as below.

$$X(t+1) = \begin{cases} X_{best}(t) - A\cdot\left|C_a X_{best}(t) - X(t)\right| & p < 0.5 \\ \left|C_a X_{best}(t) - X(t)\right|\cdot e^{bl}\cos(2\pi l) + X_{best}(t) & p \ge 0.5 \end{cases} \tag{10}$$

where p represents the probability of updating the whale position. The humpback whale will search for the prey everywhere. Here, a value A is set to be bigger than 1 or smaller than -1, which would drive the search agent to keep away from the reference whale. However, in the exploration stage, the position of the search agent is updated according to the randomly selected search agent to replace the best search agent. Finally, the WOA is allowed to implement the global search, and this can be expressed in the following.

$$X(t+1) = X_{rand}(t) - A\cdot\left|CX_{rand}(t) - X(t)\right| \tag{11}$$

where X_{rand} represents a position vector which is randomly selected from the current population.

C. Improved WOA

To enhance the optimization performance, we modified the WOA algorithm to improve the global search capability and convergence speed. This enhanced algorithm integrates four key mechanisms, including in Lévy flight strategy, nonlinear convergence factors, adaptive weighting, and reflective boundary handling. Each component is analyzed in depth below.

(1) Lévy Flight Strategy

The Lévy flight strategy is chosen to enhance the global exploration and escape local optima by introducing long-jump stochastic steps during exploitation. Lévy flight generates step sizes following a heavy-tailed distribution. The step length $L(\beta)$ is calculated as followed.

$$L(\beta) \sim \frac{\phi \cdot \mu}{|\upsilon|^{1/\beta}} \tag{12}$$

where β is stability index controlling tail heaviness, which is empirically chosen for balance between exploration and computational stability. μ and v are the average value and standard deviation of normal distributions. ϕ is the scale parameter derived from the gamma function.

$$\phi = \left[\frac{\Gamma(1+\beta) \cdot \sin(\pi\beta/2)}{\Gamma(\frac{1+\beta}{2}) \cdot \beta \cdot 2^{(\beta-1)/2}} \right]^{1/\beta} \tag{13}$$

where $\Gamma(\cdot)$ is the gamma function.

(2) Nonlinear Convergence Factor

A linear parameter a with an exponentially decreasing factor is used to balance the exploration and exploitation, which can be written in the following.

$$a = 2 \cdot e^{-t/T} \tag{14}$$

This modification ensures smooth transition between exploration and exploitation phases. In the early iterations, the a value approximates 2 to promote exploration. In the late iterations, the a value is close to be 0 in order to emphasize the exploitation. This modification could lead to smooth transition between phases avoids abrupt behavioral changes, and faster decay rate compared to linear methods accelerates exploitation.

(3) Adaptive Weighting Mechanism

The adaptive weighting mechanism is selected to adjust the influence of the best solution during position updates. The adaptive weight is written in the following.

$$w = 0.5 \cdot (1 + \cos(\pi \cdot \frac{t}{T})) \tag{15}$$

In the early iterations, the weight gains large value to enhance the global search. In the later iterations, smaller weights would accelerate the convergence.

(4) Reflective Boundary Handling

This strategy is used to maintain the population diversity by reflecting off boundaries instead of truncation, which can be expressed as below.

$$X_{new} = lb + |x - lb| \quad \mathrm{mod}(ub - lb) \tag{16}$$

where ub and lb represent the upper and lower bounds. This strategy can preserve the population diversity and avoids clustering at boundary edges.

(5) Workflow of IWOA

The whole workflow of IWOA can be classified as three steps. The first is the position initialization. The rand method is utilized to produce the initial population according to the following function.

$$X_{rand} = lb + (ub - lb) \cdot rand(1, D) \tag{17}$$

where D the is number of parameters for optimization. The second step is the position updating. For each whale i at iteration t, when $|A|<1$ happens, the position updates according the following equation.

$$X_i(t+1) = w \cdot X_{best} - A \cdot |C \cdot X_{best} - X_i(t)| \tag{18}$$

However, when $|A| \geq 1$ happens, the Lévy flight search is chosen to adjust the position which can be expressed in the following.

$$\begin{cases} X_{rand} = X_{rand} + 0.01 \cdot L(\beta) \\ X_i(t+1) = w \cdot X_{rand} - A \cdot |C \cdot X_{rand} - X_i(t)| \end{cases} \tag{19}$$

The third step is the parameter updating. The a, w, and boundary reflection should be updated at each iteration.

D. IWOA-SVM model

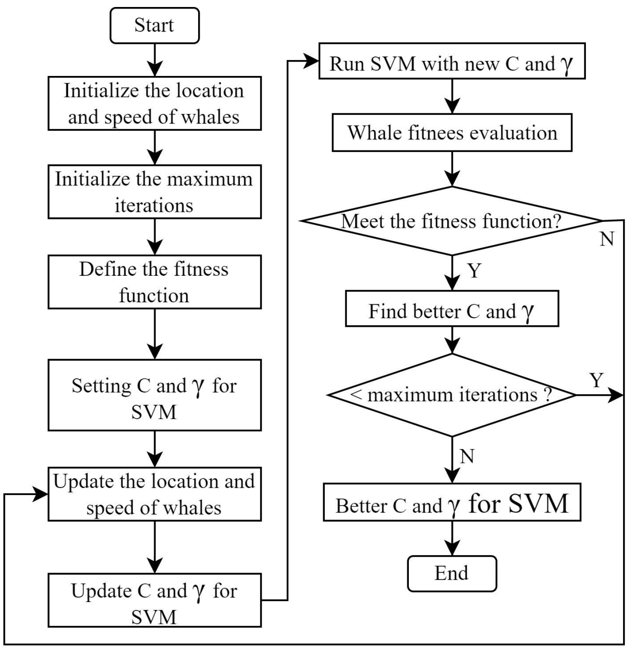


Fig. 6. Flow chart of WOA optimizaing SVM

The selection of parameters is the key step for the excellent effect of the SVM model. The C and γ in Equation (2) and Equation (3) are chosen to gain a set of optimal parameters with the smallest SVM error such that the optimized SVM is better for predictive classification. The parameters C and γ were optimized by the proposed IWOA, and the prediction model was established and shown in Figure 6. The parameters for SVM optimization by WOA are described in the following. The first step is to preprocess the experimental data to reduce noise and other interference. The second step is to initialize the population and set the algorithm parameters. The third step is to figure out the fitness value and seek the optimal solution of individual and population. The fourth step is to determine whether the algorithm meets the criteria. If 'yes', go to the next step. If 'no', go back to the third step. The last step is to substitute SVM with final parameters (C, γ) into prediction for PD diagnosis.

IV. Results and discussion

The data preparation and preprocessing are the key steps to determine the quality of SVM. Firstly, we evaluated the data samples, detected the outliers and identified the trend in the PD dataset, and selected the stable data with good periodicity to prepare the experiments. Then, considering the distribution positions of different pressure sensors, we extracted the statistical characteristics of all 16 pressure sensors. Finally, with the aim to solve the overfitting problem in the classifier, we adopted the 10-fold cross-validation technique and randomly divided the PD dataset into ten parts. Seven parts were selected to train the classifier model, and the remaining parts was utilized to test the classifier model.

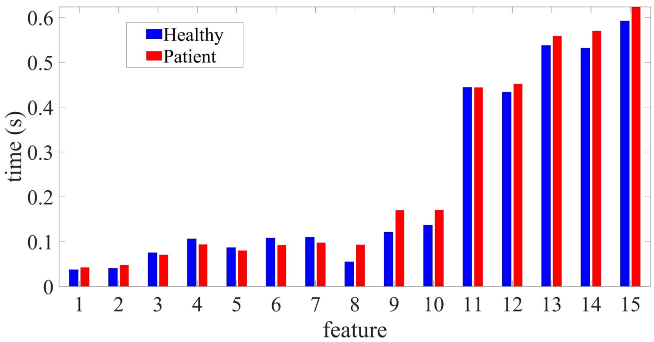


Fig. 7. Features extracted from the left foot.

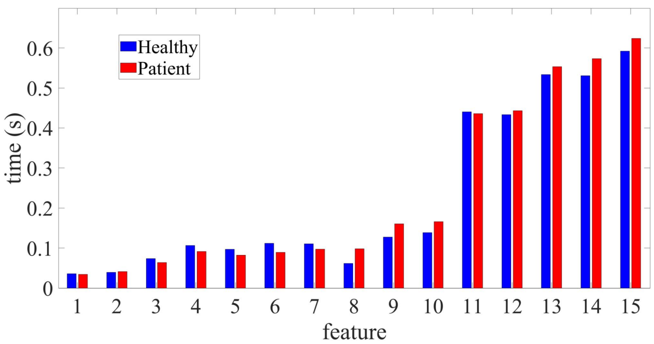


Fig. 8. Features extracted from the right foot.

Fifteen features are extracted from each foot, and shown in Figure 7 and Figure 8. Obviously, the duration of the features 3, 4, 5, 6 and 7 for the healthy are smaller than the PD patients. However, the other features present the opposite results. The feature 15 indicates the lasting time of stance phase, and the results demonstrate that the PD patients take more time for one step. The features can reveal more detailed differences for the healthy and PD patients.

TABLE IV
BEST PARAMETERS FOR DIFFERENT OPTIMIZATION ALGORITHMS

References	C	γ
SVM	0.5	15
PSO-SVM	0.5188	14.8636
GA-SVM	0.5265	14.5794
WOA-SVM	0.531	14.3573
IWOA-SVM	0.529	14.4698

For more comparative result, we chose the PSO and GA algorithms to optimize the SVM parameters. The best C and γ are shown in Table IV, and the fitness of the four optimization methods are pictured in Figure 9. It can be clearly found that the PSO method costs the least iterations to make the fitness stable, but gains the lowest final fitness value. On the contrary, The presented IWOA costs the largest iterations to stabilize the fitness, but achieve the highest final fitness value. The GA and WOA require higher final fitness value than PSO.

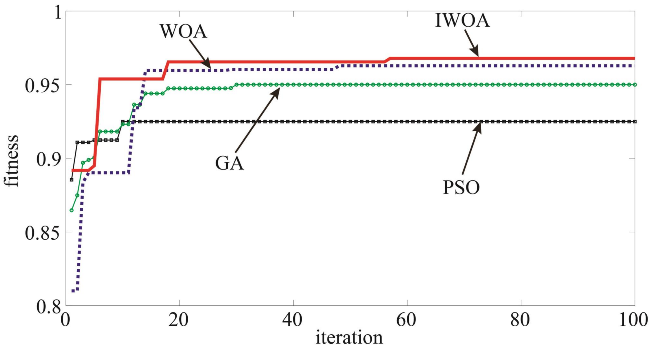


Fig. 9. Fitness of four optimization methods.

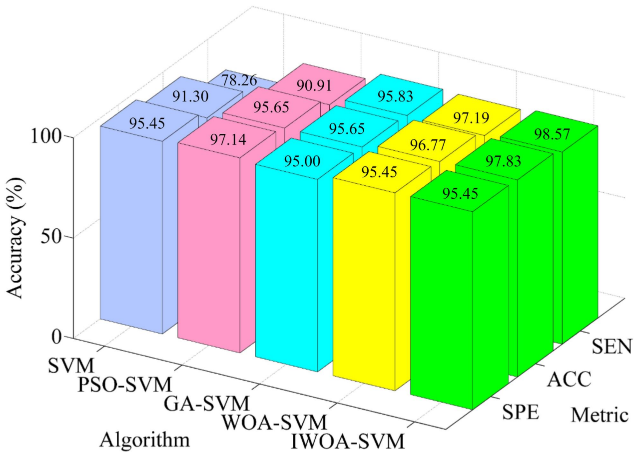


Fig. 10. Bar chart of the accuracy of PD detection

Then, we put the best parameters to the SVM, trained and tested the classifier model. The results are pictured in Figure 10. The original SVM demonstrates moderate performance, achieving an accuracy of 91.30% and specificity of 95.45%, but gains limited sensitivity (78.26%). The PSO-SVM improves sensitivity to 90.91%, and enhances the specificity to 97.14%. The accuracy is promoted to be 95.65% for PSO-SVM. The GA-SVM obtains the highest sensitivity (95.83%) among non-whale-inspired methods, while the specificity reduces to be 95%. The WOA-SVM further elevates the sensitivity to be 97.19% and the accuracy to be 96.77%, but the specificity declines to be 94.45%. The IWOA-SVM achieves the best performances of the highest sensitivity (98.57%) and accuracy (97.83%), while the specificity is maintaining at 94.45%.

TABLE V
COMPARISON WITH OTHER RESEARCHES

References	Classifier	Sen	Acc	Spe
Aditi [12]	SVM, KNN, RF	95%	91.83%	/
Ogul [13]	NR-LBP	96.8%	98.30%	97.5%
Tao Zhang [14]	EDF-EMD	/	96.54%	/
Lee and Lim [15]	NEWFM	81.10%	77.33%	65.48%
E Balaji [16]	LSTM	/	98.6%	/
This paper	IWOA-SWM	95.45%	97.83%	98.57%

Then, we compared our results with other researches. As shown in Table V, although the presented method couldn't achieve the best performance in every metric, the method used in this paper obtains competitive results in PD detection. The Oğul can utilized the neighborhood representation local binary pattern for PD detection. The transformed value is extracted in each data point, and the transformed value is set according to a user-defined criterion. However, this paper used the SVM to train a classification model for all user such that a relatively lower result is gained.

TABLE VI
COMPARISON FOR SEPARATE FOOT

	SEN	ACC	SPE
Left	97.10%	93.47%	83%
Right	95.71%	93.47%	86.36%
Left + Right	98.57%	97.83%	94.45%

Finally, we divide the thirty features into two parts as listed in Table VI. The fifteen features from the left or right feet are separately put into the SVM model with the optimal parameters by the proposed IWOA. The fifteen features from the left foot obtain the sensitivity of 97. 10%, accuracy of 93.47%, and specificity of 83%. Meanwhile, the fifteen features from the right foot obtain the sensitivity of 95. 71%, accuracy of 93.47% and specificity of 86.36%. It can be found that only fifteen features is not enough to gain higher values in terms of sensitivity, accuracy and specificity, and more features could help promote the recognition results.

V. CONCLUSIONS

This paper uses the force information to distinguish the PD sufferers and healthy persons, which is realized by the SVM classifier and WOA optimization. Firstly, we evaluated the data samples, detected the outliers and identified the trend in the dataset, and selected the stable data with good periodicity to prepare the experiment. Then, thirty features about time are extracted from both feet. The WOA is improved to optimize the SVM model, and the best parameters could be searched. In view of the possible overfitting problem of the classifier, the 10-fold cross-validation method is selected to conduct experiments and evaluate the model. In an effort to gain a comparative results, we also chose the GA and PSO algorithms to optimize the SVM model. The results showed that the IWOA-SVM method achieved the best performance in PD detection. Moreover, the presented method acquired a competitive result compared with other researches in culture.

REFERENCES

[1] S. Hayley, F. Vahid-Ansari, H. Sun, and P. R. Albert, "Mood Disturbances in Parkinson's Disease: From Prodromal Origins to Application of Animal Models," *Neurobiology of Disease*, vol. 181, p. 106115, 2023.

[2] A. S. Monaghan, E. Gordon, L. Graham, E. Hughes, D. S. Peterson, and R. Morris, "Cognition and Freezing of Gait in Parkinson's Disease: A Systematic Review and Meta-Analysis," *Neuroscience and Biobehavioral Reviews*, vol. 147, p. 105068, 2023.

[3] A. Ponsoni, A. V. Sardeli, F. P. Costa, and L. F. Mourão, "Prevalence of Sarcopenia in Parkinson's Disease: A Systematic Review and Meta-Analysis," *Geriatric Nursing*, vol. 49, pp. 44-49, 2023.

[4] A. Rana, A. Dumka, R. Singh, M. K. Panda, N. Priyadarshi, and B. Twala, "Imperative Role of Machine Learning Algorithm for Detection of Parkinson's Disease: Review, Challenges and Recommendations," *Diagnostics*, vol. 12, no. 8, p. 2003, 2022.

[5] B. Vidya, and P. Sasikumar, "Gait Based Parkinson's Disease Diagnosis and Severity Rating Using Multi-Class Support Vector Machine," *Applied Soft Computing*, vol. 113, p. 107939, 2021.

[6] D. Joshi, A. Khajuria, and P. Joshi, "An Automatic Non-Invasive Method for Parkinson's Disease Classification," *Computer Methods and Programs in Biomedicine*, vol. 145, pp. 135-145, 2017.

[7] W. Zeng, F. Liu, Q. Wang, Y. Wang, L. Ma, and Y. Zhang, "Parkinson's Disease Classification Using Gait Analysis via Deterministic Learning," *Neuroscience Letters*, vol. 633, pp. 268-278, 2016.

[8] I. El Maachi, G.-A. Bilodeau, and W. Bouachir, "Deep 1D-ConvNet for Accurate Parkinson Disease Detection and Severity Prediction from Gait," *Expert Systems with Applications*, vol. 143, p. 113075, 2020.

[9] M. W. Creaby, and M. H. Cole, "Gait Characteristics and Falls in Parkinson's Disease: A Systematic Review and Meta-Analysis," *Parkinsonism and Related Disorders*, vol. 57, pp. 1-8, 2018.

[10] J. Figueiredo, C. P. Santos, and J. C. Moreno, "Automatic Recognition of Gait Patterns in Human Motor Disorders Using Machine Learning: A Review," *Annual Review of Biomedical Engineering*, vol. 53, pp. 1-12, 2018.

[11] Z. K. Senturk, "Early Diagnosis of Parkinson's Disease Using Machine Learning Algorithms," *Medical Hypotheses*, vol. 138, p. 109603, 2020.

[12] A. Govindu, and S. Palwe, "Early Detection of Parkinson's Disease Using Machine Learning," *Procedia Computer Science*, vol. 218, pp. 249-261, 2023.

[13] O. C. Yurdakul, M. S. P. Subathra, and G. S. Thomas, "Detection of Parkinson's Disease from Gait Using Neighborhood Representation Local Binary Patterns," *Biomedical Signal Processing and Control*, vol. 62, p. 102070, 2020.

[14] T. Zhang, Y. Zhang, H. Sun, and H. Shan, "Parkinson Disease Detection Using Energy Direction Features Based on EMD from Voice Signal," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 1, pp. 127-141, 2021.

[15] S. H. Lee, and J. S. Lim, "Parkinson's Disease Classification Using Gait Characteristics and Wavelet-Based Feature Extraction," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7338-7344, 2012.

[16] E. Balaji, D. Brindha, V. K. Elumalai, and R. Vikrama, "Automatic and Non-Invasive Parkinson's Disease Diagnosis and Severity Rating Using LSTM Network," *Applied Soft Computing*, vol. 108, no. 4, p. 107463, 2021.

[17] A. Benba, A. Jilbab, A. Hammouch, and S. Sandabad, "Voiceprints Analysis Using MFCC and SVM for Detecting Patients with Parkinson's Disease," *Proceedings of the International Conference on Electrical and Information Technology*, 2015.

[18] S. Zayrit, D. B. Taoufiq, B. Nsiri, Y. Korkmaz, and A. Ammoumou, "The Detection of Parkinson Disease Using the Genetic Algorithm and SVM Classifier," *Applied Acoustics*, vol. 171, p. 107528, 2021.

[19] L. Jin, Q. Zeng, J. He, Y. Feng, S. Zhou, and Y. Wu, "A ReliefF-SVM-Based Method for Marking Dopamine-Based Disease Characteristics: A Study on SWEDD and Parkinson's Disease," *Behavioural Brain Research*, vol. 356, pp. 400-407, 2019.

[20] Y. H. Xie, G. S. Mi, D. Tan, and C. N. Liu, "WOA-XGBoost Based Railway Accident Type Prediction and Cause Analysis," *Engineering Letters*, vol. 33, no. 3, pp. 732-742, 2025.

[21] R. H. Zhou, Y. Zhang, X. D. Sun, H. N. Liu, and Y. Y. Cai, "MSWOA: Multi-strategy Whale Optimization Algorithm for Engineering Applications," *Engineering Letters*, vol. 32, no. 8, pp. 1603-1615, 2024.

[22] F. Liang, L. Sun, Z. Zeng, and J. Kang, "Treatment of Surfactant Wastewater by Foam Separation: Combining the RSM Method and WOA-BP Neural Network to Explore Optimal Process Conditions,"

Chemical Engineering Research and Design, vol. 193, pp. 85-98, 2023.

[23] M. Yu, D. Niu, K. Wang, R. Du, X. Yu, L. Su, and F. Wang, "Short-Term Photovoltaic Power Point-Interval Forecasting Based on Double-Layer Decomposition and WOA-BiLSTM-Attention and Considering Weather Classification," *Energy*, vol. 275, 2023.

[24] U. Kose, "A Hybrid SVM-WOA Approach for Intelligent Fault Diagnosis Applications," *Proceedings of the Innovations in Intelligent Systems and Applications Conference*, 2019.

[25] S. Samantaray, and A. Sahoo, "Prediction of Suspended Sediment Concentration Using Hybrid SVM-WOA Approaches," *Geocarto International*, vol. 37, no. 19, pp. 5609-5635, 2021.

[26] A. Sahoo, and D. K. Ghose, "Application of Hybrid Support Vector Machine Model for Streamflow Prediction in Barak Valley, India," *Earth and Environmental Science Transactions of the Royal Society*, vol. 1032, no. 1, 2022.

[27] D. Kong, Y. Chen, N. Li, C. Duan, L. Lu, and D. Chen, "Tool Wear Estimation in End Milling of Titanium Alloy Using NPE and a Novel WOA-SVM Model," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 7, pp. 5219-5232, 2020.