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A fall risk assessment model based on PSO-GWO optimization strategy

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Abstract: *Falls are the main factor leading to hospitalization among the elderly, and making the prediction of fall risk and timely intervention treatment is the key to achieve healthy aging. In fall risk assessment, common methods at home and abroad include questionnaire, scale, and statistical methods. This paper combines multi-dimensional gait parameters and machine learning algorithms to realize the quantitative assessment and accurate prediction of fall risk. Predict fall risk by building and optimizing machine learning models based on gait analysis. The research work covers the construction of fall risk prediction model, algorithm improvement and comparative analysis. Ninety-seven eligible participants from Foshan People's Hospital were included to collect data on gait parameters during single task (standard walking) and dual task (performing cognitive task) states. Through analyzing the collected data, the key gait factors affecting the fall risk in the elderly were deeply explored. We found that single-task step frequency, single-task foot following angle and single-task foot following angle symmetry parameters are closely related to fall risk. In order to further improve the prediction performance, this study proposed a new hybrid optimization strategy, PSO-GWO-LightGBM. The PSO algorithm effectively enhances the global exploration ability of the algorithm and suppresses the early convergence to the suboptimal solution, thus helping the LightGBM model to obtain a good parameter space, avoiding the premature local optimal in the model training process, and accelerating the convergence process of the model. In addition, GWO Wolf pack social hierarchy and collaboration mechanism are added to provide strong local search and fast convergence ability, and help the model to adjust the iterative process. The improved nonlinear convergence factor helps the overall algorithm to re-expand the parameter search space in the late iteration, which facilitates the model to jump out of the local optimum and improve the convergence accuracy. The experimental results showed that the PSO-GWO optimized LightGBM model achieved a significant improvement in the accuracy and generalization ability of fall risk prediction.*

Keywords: *Gait; Fall Risk Prediction; Machine Learning; Single Task; Dual Task.*

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I. INTRODUCTION

Globally, the aging phenomenon of the population is becoming increasingly significant. The study predicts that between 2000 and 2050, the number of people aged 60 and over will rise sharply from 605 million to 2 billion （Bo et al., 2021）. According to the results of the seventh national census, the number of people aged 60 and over in China accounted for 18.70 percent by the end of 20 20. In this part of the population, the proportion of elderly people aged 65 years and over in the total population was 13.5% (China Statistics., 2021). Analysts estimate that as the aging trend deepens, more exceed 30 percent (He et al., 2018) by 2050. In urban areas of China, the proportion of falls among the elderly is between 15.7% and 23.5% (Gao et al., 2023), the living environment of the rural elderly is more difficult, and the incidence of falls may be higher. It is important to study machine learning models based on gait analysis to predict fall risk. This fall risk prediction model can make full use of the patient's gait data, combine the advantages of machine learning algorithms, can more accurately predict fall risk, and provide scientific basis for personalized prevention and intervention measures, which can achieve real-time online assessment.

Dual-task performance is widely considered an effective approach in assessing the effects of cognitive-motor interaction. When the cognitive burden in the two tasks performed exceeds the individual cognitive capacity, the performance of both the primary and secondary tasks, or both, may be affected (Leone et al., 2017). When performing dual-task walking, extra attention demands are called dual-task costs (Dual Task Cost, DTC), which quantify the need for cognitive resources by comparing the difference between a single task and dual-task performance. Numerous studies have shown a clear association between an increase in cognitive costs and an increased risk of falls (McIsaac et al., 2015; Zukowski et al., 2021; OKeefe et al., 2021; Piche et al., 2023).

Some scholars found that older people had a higher risk of falling outdoors than indoors, male elderly people had a higher risk of falling in the home environment, and the opposite was true outdoors(Ding et al., 2018). Menant et al showed that older people wearing slippers were more likely to fall than those who were barefoot or wearing conventional shoes(Menant et al., 2008; Xiang et al., 2021).

Palmerini et al. Through analyzing a large number of fall data in real environment, proposed a machine learning algorithm based on the multi-stage fall model, designed a new overlapping window technology based on the normalized signal peak time, all of the features are extracted from the acceleration paradigm, does not depend on the direction of the sensor, can provide accurate window for feature extraction, ensure the reliability and availability of data(Palmerini et al., 2020). Quadros et al. proposed a wristband fall detection method, combining different sensors, signals and direction components (vertical and not vertical), using a set of integrated method based on threshold and machine learning to determine the best method of fall detection, using threshold Madgwick decomposition method and machine learning method, verify the machine learning in practical application method than threshold method(Quadros et al., 2018).

II. EXPERIMENTAL PROCEDURE

2.1 Participator

From the end of 2020 to the beginning of 2021,102 elderly people were first recruited from Foshan First People's Hospital. After screening, 97 participants met the criteria.

Screening criteria for participants: (1) aged 55 years and older; (2) good cognitive function; (3) no recent major surgery and ability to walk independently or assisted equipment; (4) willing to participate in the study and signed informed consent.

Exclusion criteria included: (1) neurodegenerative disorders that may affect cognitive or motor function; (2) taking antipsychotics or benzodiazepines, or having a severe mental condition problem, such as deep depression or severe anxiety.

2.2 Clinical and fall assessment

Prior to the start of the experiment, clinicians conducted preliminary fall risk assessments for all participants using the Falls Risk Assessment Scale for the Elderly issued in 2011 by the Ministry of Health of China. The distribution of people in each interval of fall risk scores is shown in Figure 2.1.

Fig. 2.1 Number of falls risk scores

2.3 Data acquisition

Gait data acquisition was selected to complete three gait tests in a horizontal corridor with the help of a Jibuen wearable gait acquisition device. The includes shoes and wearable modules equipped with inertial MEMS (Microelectromechanical system) sensors attached to the bottom of the heel, the upper and lower limbs, and the back of the wrist to capture motion signals and transmit them to the computer. Data pre-processing uses high-order low-pass filters and hexahedral calibration techniques to reduce high-frequency noise interference and mounting errors generated by the sensor device. Furthermore, the cumulative error was corrected based on the zero-correction algorithm. The final gait parameters were obtained by merging acceleration data and pose (calculated using a quaterion complementary filtering technique)(Gao et al., 2021; Tao et al., 2018; Xie et al., 2019).

Gait trials consisted of one single-task test and two two-task tests. Single-task walking (ST) is normal walking. The dual-task walk (DT) consists of two items: calculating a multiple of 7 and counting backward from 100. For calculating a multiple of 7, participants counted while walking (e. g. 7,14,21, etc.) and counted down from 100 (e. g., 100,99,98, etc.). The collected gait parameters and their introduction are as follows: the stride length is the distance between the same leg from the foot following the ground and the foot following the ground again. Step speed is the distance moved in the forward direction per unit of time. Step frequency indicates the number of steps per minute. The support phase occupies most of the gait cycle, starting with the ground of the foot of one foot until the toe of the foot ends off the ground. The swing phase starts from the toe of a foot off the ground until the foot follows the ground again. Step time is the duration between the same leg following the foot and the next one. The swing time is the time period when the foot leaves the ground during the gait cycle. Support time is the period of the foot contact with the ground in the gait cycle. Toe Angle from the ground: the Angle between the toe and the ground when the foot is ready to leave the ground. The foot follows the ground Angle: the Angle of the heel to the ground when the foot is about to touch the ground.

2.4 Fall risk factor analysis

To deeply investigate the key features affecting the risk of falls, the recursive feature elimination (RFE) technique was used. RFE is an effective feature selection method by gradually removing less important features and standardizing only the features most relevant to the target variable. In this way, we screened the optimal feature combination for various machine learning models, ensuring that the features input to the model are not only concise but also highly representative. Figure 2.2 shows the importance ranking of each feature in the fall prediction model, where the abscissa indicates how much this feature contributes to the prediction results. The top 10 features are listed in the figure, and the top three features are single-task step frequency, single-task foot ground angle and single-task foot ground angle symmetry. These characteristics have significant effects in predicting the risk of falls. Single-task step frequency, single-task ground angle and single-task ground angle symmetry may be related to subject balance and walking stability.

Fig. 2.2 Feature importance ranking of RFE

We use our partial dependency maps (PDP) to illustrate the impact of single-task step frequency, single-task foot ground angle, and single-task foot ground angle symmetry on predicted fall risk values. As can be seen from Figure 2.3 that the single-task step frequency has a very limited effect on the model prediction results when the standardized value is less than 0, and the eigenvalue change has little effect on the fall prediction results. The effect of 0 and 0.25 on the model predicted fall risk value increased significantly and was positively correlated with the predicted score line, with almost no effect on the prediction.

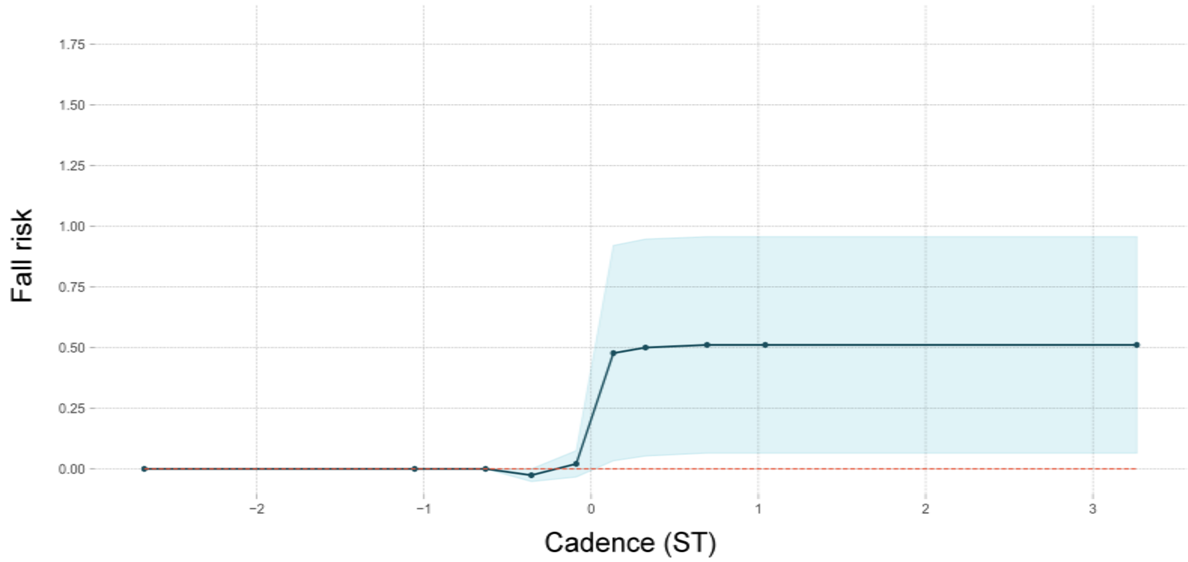

Fig. 2.3 PDP of Cadence under Single-Task Condition

As can be seen from Figure 2.4 , when the eigenvalue increases from 0 to 1, the influence of the single-task foot follows the ground angle on the model prediction increases significantly, showing a clear downward trend, which indicates that the single-task foot follows the ground angle and the fall wind. The effect of the single-task step frequency between 0 and 0.25 was significantly increased on the model predicted fall risk value and was positively correlated with the predicted score line, with almost no effect on the prediction in the other value fields.

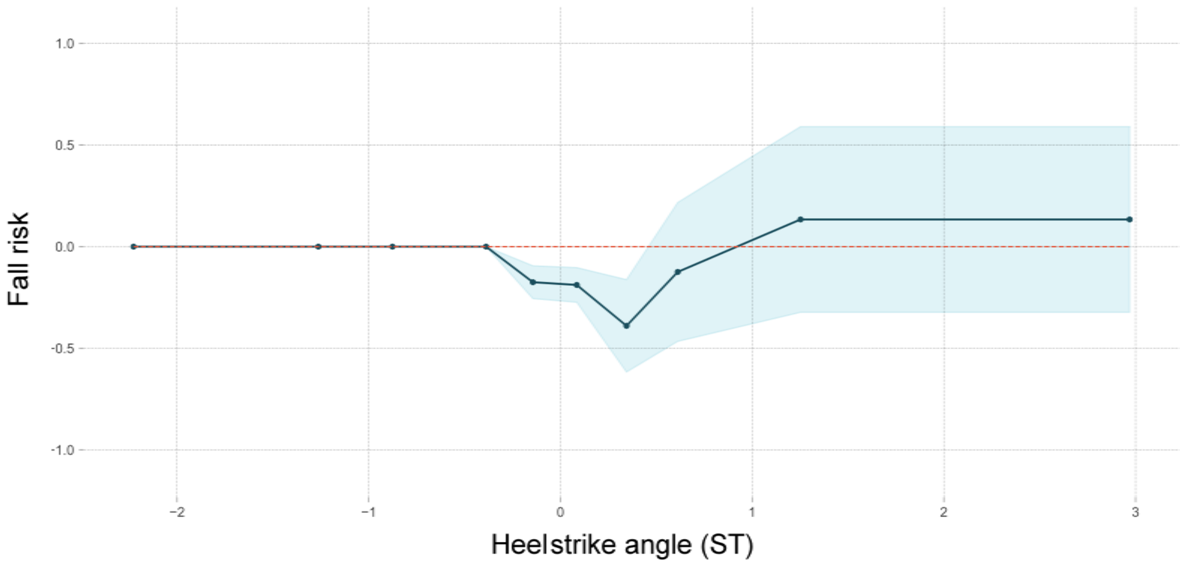

Fig. 2.4 PDP of Heel Strike Angle under Single-Task Condition

As can be seen from figure 2.5, when the single task with ground angle symmetry in 0 to 0.3, with the effect of the single task with ground angle symmetry on the model prediction fall risk value increased significantly, and negatively correlated with the prediction score line, and away from the 0 interval, partial dependence variation is relatively flat, indicating that the influence of symmetry on the model prediction results is relatively small.

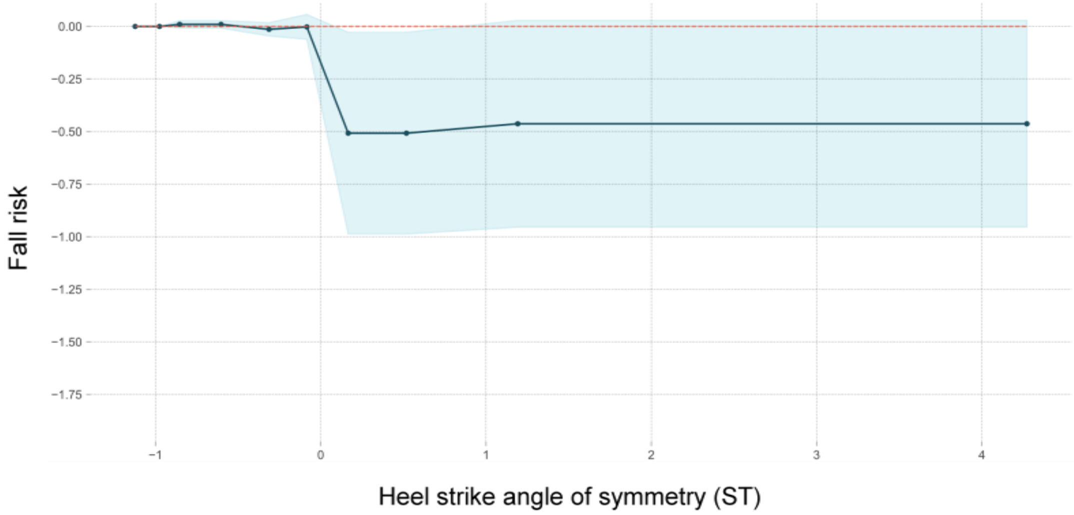

Fig. 2.5 PDP of Heel Strike Angle Symmetry under Single-Task Condition

2.5 The LightGBM algorithm based on the PSO-GWO optimization

Based on the shortcomings of the existing methods, this chapter introduces the PSO-GWO algorithm to optimize the LightGBM. PSO (Particle swarm optimization algorithm) and GWO (Grey Wolf optimization algorithm), as two widely used swarm intelligent optimization algorithms, perform well in solving complex optimization problems. The PSO algorithm draws on the behavior of the flock foraging to search for the optimal solution by the movement of the particles in the solution space. The GWO algorithm simulates the social level and behavior of wolves' hunting, and optimizes the objective function through the cooperation of wolves. Considering the advantages of these two algorithms, we tried to combine them and propose a PSO, which was combined with the GWO algorithm to optimize the parameters of the LightGBM model, in order to further improve the performance of the model in the fall risk prediction task.

The feasibility of combining the PSO algorithm and the GWO algorithm to optimize the LightGBM model parameters and predict the fall risk value is mainly reflected in the following aspects:

(1) The PSO algorithm can better balance the global exploration and local development capability of the algorithm, and improve the convergence speed and optimization accuracy. This provides strong support for optimizing the parameters of the LightGBM model.

(2) The GWO algorithm simulates the Wolf pack hierarchy and hunting behavior, and leads other wolves to optimize the search through □, □ and γ wolves. The algorithm has strong global search ability and convergence speed to effectively avoid falling into local optima. Combining it with the PSO algorithm can further enhance the optimized performance of the algorithm.

(3) The LightGBM model has the advantages of fast training speed and good generalization performance, and has shown good performance in the fall risk prediction task. Optimizing its parameters by PSO and GWO algorithms is expected to further improve the prediction accuracy of the model.

Considering the characteristics of the PSO algorithm and the GWO algorithm, and the performance of the LightGBM model in the fall risk prediction task, combining the two algorithms to optimize the LightGBM model parameters has high feasibility. This is particularly important for optimizing the hyperparameters of LightGBM models, because efficient and accurate hyperparameter search can greatly improve the performance of the model on complex datasets, and by building the PSO-GWO-LightGBM model, it can improve the accuracy of fall risk value prediction.

2.5.1 The PSO-GWO hybrid strategy

The PSO algorithm uses the historically optimal information of individuals and groups to guide the search direction and has strong global search capability. However, it may sometimes converge prematurely to the local optimal solution, especially when dealing with complex problems. The GWO algorithm realizes a population-based optimization search by simulating the social hierarchy and hunting behavior of gray wolves. It is particularly good at local search, and can finely adjust the search direction to approximate the optimal solution. Combining PSO and GWO into PSO-GWO composite algorithm can make full use of PSO and local search capability of GWO to complement each other. In the search process, PSO can help GWO jump out of the possible local optimal trap, while GWO can conduct fine search near the better solution found by PSO, thus improving the quality of search efficiency and reconciliation.

(1) Improved nonlinear convergence factor

The convergence factor of the grey Wolf algorithm is a key parameter, which balances the global exploration and local development capability of the algorithm. Its value usually decreases linearly from 2 to 0 with the number of iterations. However, this linear decreasing strategy may not always be the most effective, because the behavior of the algorithm in the convergence process is not linear. The linear decrease may lead the algorithm to reduce the exploration range prematurely in the early stage of the search, or still maintain a large exploration range in the later stage of the search, thus affecting the convergence speed and accuracy of the algorithm. The modified non-linear convergence factors are as follows:

$$a = \frac{\mu}{1+e^{-\varepsilon\frac{t}{T}}} \tag{2.1}$$

In the above equation, μ and ε are two parameters affecting the nonlinear change of the control parameter a. Figure 2.6 shows the convergence factors before the modification, and Figure 2.7 shows the modified convergence factors.

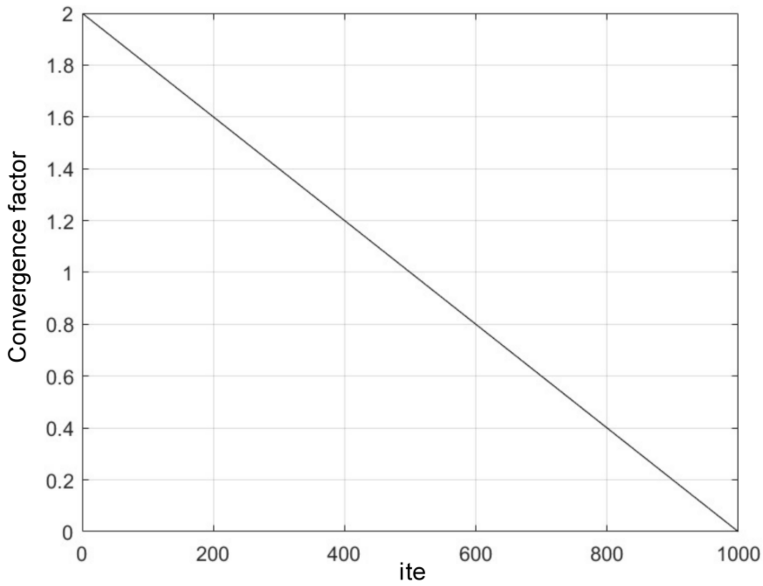

Fig. 2.6 Original convergence factor

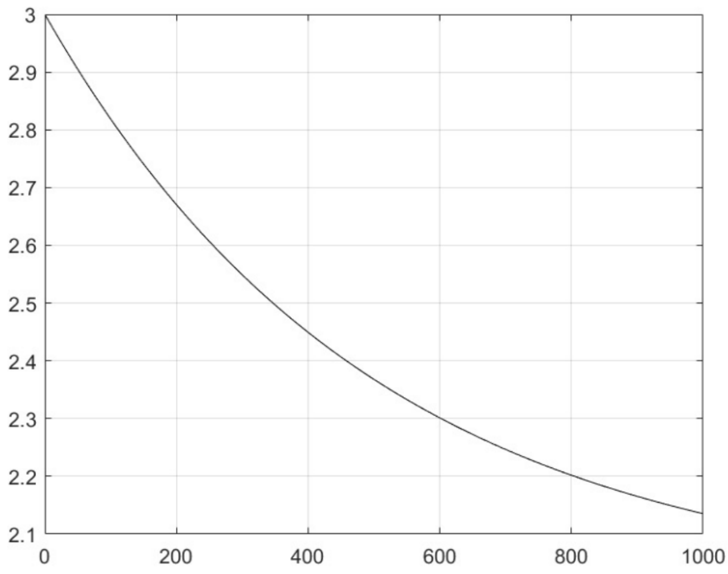

Fig. 2.7 Modified convergence factor

(2)Adaptive update policy

Since the particles will only move in the direction of their individual optima, it is easy to fall into the local optimal solution without escape. This can lead algorithms to difficulties in finding global optimal solutions, especially in functions with multiple local extreme points. When facing large-scale problems, PS may require a lot of computational time to find the optimal solution. Moreover, due to the lack of dynamic regulation of speed, the convergence accuracy of the algorithm may be low and difficult to converge. In this paper, we combine the search strategy of GWO algorithm to optimize the search process of PSO algorithm.

$$v_i^{(t+1)} = \omega \cdot v_i^{(t)} + c_k \cdot r \cdot \left(x_k - x_i^{(t)}\right) \tag{2.2}$$

$$K = \alpha, \beta, \gamma \tag{2.3}$$

Where r is a random vector whose components are evenly distributed between [0,1].$c_k$is the adaptive weight, the specific formula is as follows:

$$C = b\frac{F(k)}{F(\alpha)+F(\beta)+F(\gamma)} \tag{2.4}$$

Where b is the parameter obtained after the tuning.

2.5.2The PSO-GWO algorithm flow

The following is the PSO-GWO algorithm. The specific implementation steps of PSO-GWO algorithm are as follows:

Step 1: Initialize the algorithm parameters and generate the initialized population in the problem space.

Step 2: Use the immune selection mechanism to calculate the individual fitness value, and record the first three individuals according to the idea of the grey Wolf algorithm, recording the first three individuals as α 、β and δ

Step 3: Iteratively update the nonlinear convergence factor a , and update the position of each searched individual according to the update strategy of the particle swarm algorithm.

Step 4: Use the relative base learning mechanism to exchange information between individuals so as to constantly approach the optimal position.

Step 5: Update the population with the adaptive variation operation. At the same time, it determines whether the algorithm has reached the maximum number of iterations. If it is, the global optimal individual is output, otherwise, the algorithm iteration is repeated from step 2.

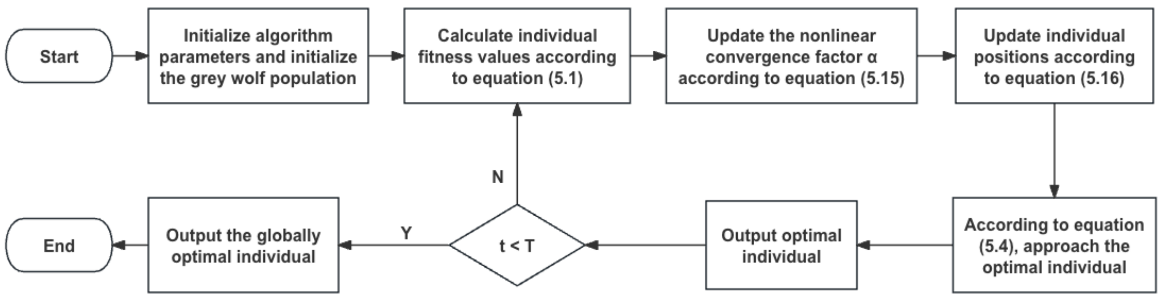

Fig.2.8 Flowchart of the PSO-GWO Algorithm

2.5.3 Improved LightGBM model based on the PSO-GWO algorithm

This section will further combine the PSO-GWO algorithm with the LightGBM model to construct an efficient fall risk prediction model.

The main idea of the PSO-GWO-LightGBM model is to use the PSO-GWO algorithm to optimize the hyperparameters of the LightGBM model. Specifically, we encode the hyperparameters of the LightGBM model (learning rate, maximum tree depth, maximum number of leaf nodes, etc.) as the particle positions in the PSO-GWO algorithm, and search for the optimal hyperparameter combination through iterative optimization.

LightGBM is a decision tree algorithm based on gradient lifting, whose performance largely depends on the choice of its hyperparameters.

The following table is the five key parameters for optimizing the LightGBM by PSO-GWO. The values of these five parameters were encoded as the particle positions in the PSO, and the modified algorithm was used to search for the optimal values of these five parameters. In each iteration, the position of the current particle is used to configure the LightGBM, and its performance is evaluated on the validation set. The fitness value of the particle can be defined as the negative validation error of LightGBM. According to the particle fitness values, the velocity and position of the particles, and the positions of the α、 β and γ wolves.

In this way, we efficiently search the hyperparameter space and find a set of parameter values, enabling the optimal performance of LightGBM on the validation set. The PSO-GWO-LightGBM flowchart is shown in Figure 2.9 below.

Tab. 2.1 Five key parameters of LightGBM optimized through PSO-GWO

Hyperparameter name	Windows default	Optimum
learning rate	0.1	0.049
Maximum depth of the tree	-1	5
The maximum number of leaf nodes	31	213
Feature sampling ratio	1.0	0.5
Data sampling ratio	1.0	0.8

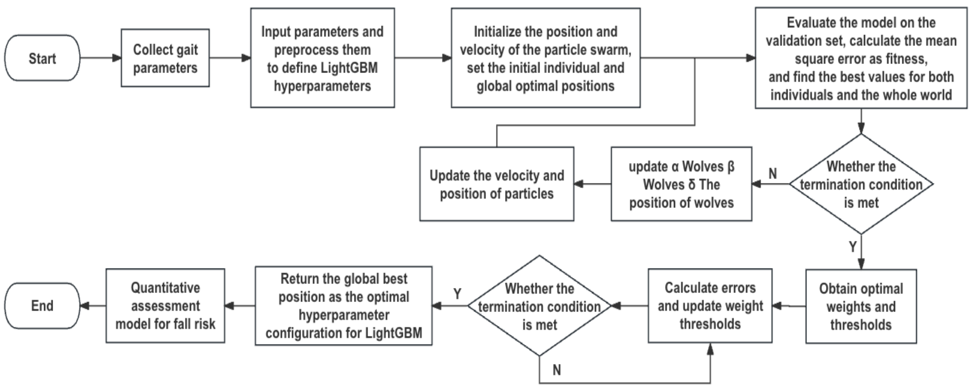

Fig. 2.9 PSO-GWO-LightGBM flow chart

After adjusting the LightGBM model parameters using the PSO-GWO optimization algorithm, the fall risk value is predicted using the preset parameter configuration of the model. The specific prediction results and the comparison between the true and predicted values can be viewed in the detailed data in Table 2.2 and visually displayed in the form of scatter plot in Figure 2.10.

Tab. 2.2 Prediction results of fall risk value using PSO -GWO-LightGBM model

Model name	MSE	RMSE	R-Square
PSO-GWO- LightGBM	0.5391	0.7343	0.8011

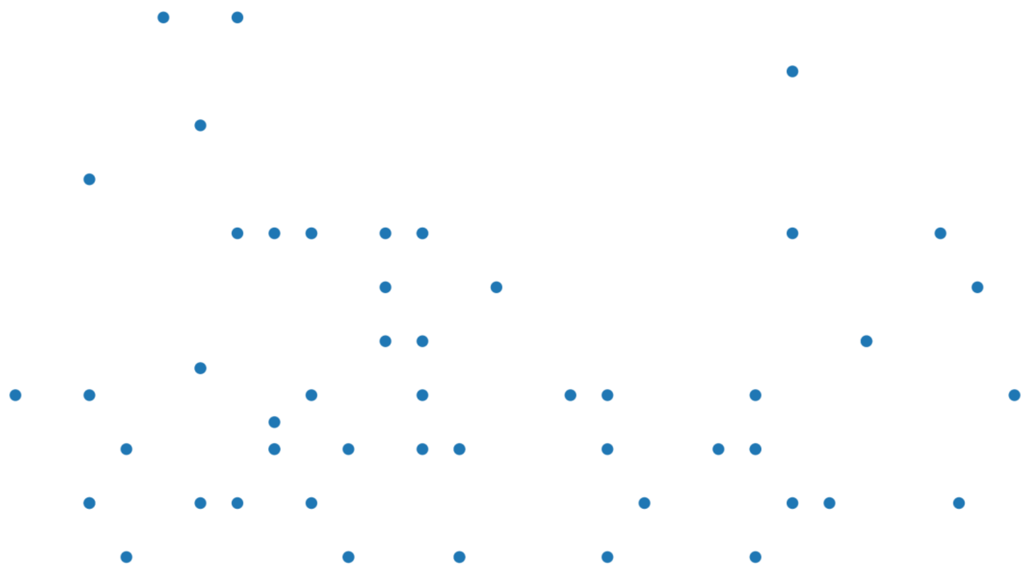

Fig. 2.10 Scatter plot of PSO -GWO-LightGBM prediction results

III. RESULTS AND DISCUSSIONS

To verify the accuracy and effectiveness of the algorithm, the model with the classical optimization algorithm.

Tab. 3.1 HY -LightGBM、RS -LightGBM、GA -LightGBM、LightGBM、PSO -GWO-LightGBM prediction comparison

Model name	MSE	RMSE	R-Square
HY -LightGBM	0.6712	0.8193	0.6842
RS -LightGBM	0.6879	0.8294	0.5413
GA -LightGBM	0.6923	0.8321	0.4652
LightGBM	0.7177	0.8472	0.6019
PSO-GWO- LightGBM	0.5391	0.7343	0.8011

Fig. 3.2 PSO -GWO-LightGBM, LightGBM, GA -LightGBM, RS -LightGBM, HY -LightGBM prediction comparison chart

The experimental results show that among the four models, the LightGBM model (PSO-GWO-LightGBM) optimized by PSO-GWO algorithm has the best evaluation indexes in the mean square error (MSE), the root mean square error (RMSE), and the coefficient of determination (R-Square). Its MSE value is 0.5391, RMSE value is 0.7343, and R-Square value is 0.8011, which indicates that the PSO-GWO-LightGBM model has a significant improvement in the accuracy of fall risk prediction when compared with other models. Its efficient global search ability, mechanism to prevent premature convergence and strategy to optimize hyperparameters work together to show stronger performance in the fall risk prediction task. This also demonstrates the effectiveness and superiority of the PSO-GWO algorithm in dealing with complex parameter optimization problems.

IV. CONCLUSION

In this study, we proposed a PSO-GWO-LightGBM, a LightGBM model optimization strategy based on immune particle swarm optimization and grey Wolf optimization algorithm. The PSO algorithm effectively enhances its global search capability. At the same time, by combining with the GWO algorithm, the exploration and development ability of the algorithm are further balanced. The PSO algorithm selects the parameter space of the LightGBM model through the immune selection mechanism, dynamically adjusts the diversity of parameter combinations, and avoids the model training. The relative basis learning mechanism helps to communicate and share search information between different parameter combinations, which accelerates the convergence process of the model. The improved nonlinear convergence factor helps the overall algorithm to re-expand the parameter search space later in the iteration period, which facilitates the model to jump out of the local optimum and improve the convergence accuracy. The social hierarchy strategy of the GWO algorithm leads the whole parameter population to search for the optimal solution, which further improves the performance of the LightGBM model. Through a series of comparative experiments, PSO-GWO-LightGBM has achieved significant improvement in the prediction accuracy, stability and generalization ability, which provides new ideas and methods for the intelligent assessment of fall risk.

Conflict of interest

There is no conflict to disclose.

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