Heuristic Intelligent Algorithm-Based Approach for In-Depth Development and Application Analysis of Micro- and Nanoembedded Systems

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***Abstract*—Developing application analysis and testing methods is an important part of the in-depth development of micro-nano embedded systems under complex integrated architectures. Therefore, the research on application analysis and testing models is of great significance for the in-depth development and efficient design of embedded systems. In order to fully explore the effective information of test analysis data in the in-depth development of micro-nano embedded systems under complex integrated architectures and improve the analysis and prediction accuracy of test analysis models, a development test analysis model based on the photon search algorithm and LightGBM is proposed. First, the development process of micro-nano embedded systems under complex integrated architectures is analysed, and a system analysis architecture is designed to propose test analysis factors. Second, a development test analysis model is established by combining the photon search algorithm and LightGBM. Subsequently, the feasibility and efficiency of the model are proposed by analysing the data of the development process. The analysis of data examples shows that the LightGBM test analysis model has high analysis and prediction accuracy and generalisation performance.**

***Keywords*—Photon search algorithm; deep development of micro- and nanoembedded systems; application test and analysis methodology; LightGBM**

I. Introduction

With the continuous development of microelectronics technology, the application of micro-nano embedded systems in various industries is becoming more and more widespread, especially in the fields of Internet of Things, intelligent sensing, healthcare, and communication technology [1]. With the increased complexity and computational volume of micro-nano embedded system applications, the development of micro-nano embedded systems is becoming more and more difficult, which leads to an increased probability of security risks in the iterative updating of development and application work [2]. At the same time, the micro-nano embedded system application function diversification makes the micro-nano embedded system development workers in-depth design and development, which leads to the micro-nano embedded system test and evaluation index feature dimension increase, the traditional test algorithm cannot build complex model relationship [3]. In order to alleviate the problems of insufficient testing means and insufficient accuracy, the system design-oriented development application test and analysis model intelligence has become a development trend [4]. Therefore, the study of constructing an efficient development and application test analysis model has received more and more attention from experts and scholars, which is of great significance for the development of micro and nano embedded systems to solve the problem in reality.

The deep development and application analysis intelligence of micro and nano embedded systems under complex integrated architecture improves the design efficiency in two main aspects, i.e., deep intelligent development of system and intelligent testing of application analysis [5]. System deep intelligent development requires high fidelity mathematical models and also high precision model generation methods [6]. Micro-nano embedded system development application analysis intelligent testing is an important part of the development and design process, generally using test analysis algorithms to simulate the system development and testing process [7]. Currently, test analysis algorithms include hierarchical analysis method [8], expert system method [9], neural network method [10], integrated learning method [11], deep learning method [12] and so on. Since the process of in-depth development of micro-nano embedded systems under complex integration-oriented architecture is a complex process with high dimensionality of relevant data parameters, current test analysis algorithms are unable to construct accurate test results, and the real-time nature of test analysis is unable to meet the demand [6-13]. In addition, test analysis algorithms in the complex integration architecture of micro-nano embedded systems in the depth of the development process is relatively small, in order to improve the design efficiency, need to design targeted test analysis algorithms [6-14]. In this paper, the initial choice of integrated learning algorithm is taken to construct the test analysis algorithm, but the integrated learning algorithm is easy to fall into the local optimum in the learning training in the problem of high dimensionality and complex process, therefore, the debugging optimization of the designed test analysis algorithm is needed [15].

In view of the above problems, this paper proposes a development test analysis algorithm based on intelligent optimization algorithm and integrated learning technology around the deep development process of micro-nano embedded system under complex integration architecture. For the development and test analysis problem, the mechanism of the deep development process of micro-nano embedded system under the complex integration architecture is analyzed, and the relevant test and analysis parameters are extracted; for the development and test analysis model construction problem, the hyperparameters of lightweight gradient lifter are optimized by combining with photon search algorithm, and the development and test analysis model based on photon search algorithm to improve lightweight gradient lifter is put forward; and the development and test analysis method put forward has high analysis and prediction accuracy and generalization performance through the application of examples. The proposed development test analysis method has high analysis and prediction accuracy and generalization performance, which provides a new method for the in-depth development process testing of micro-nano embedded systems under the complex integration architecture.

II. In-Depth Development of Micro- and Nano-Embedded Systems for Complex Integrated Architectures

A. System Architecture

1) Micro-nano embedded system: Micro-nano embedded systems are embedded systems that integrate microelectromechanical systems and nanotechnology. These systems usually contain micromechanical devices, sensors, actuators, and electronic circuits, which can vary in size from the micron to the nanometer level [16], as shown in Fig. 1.

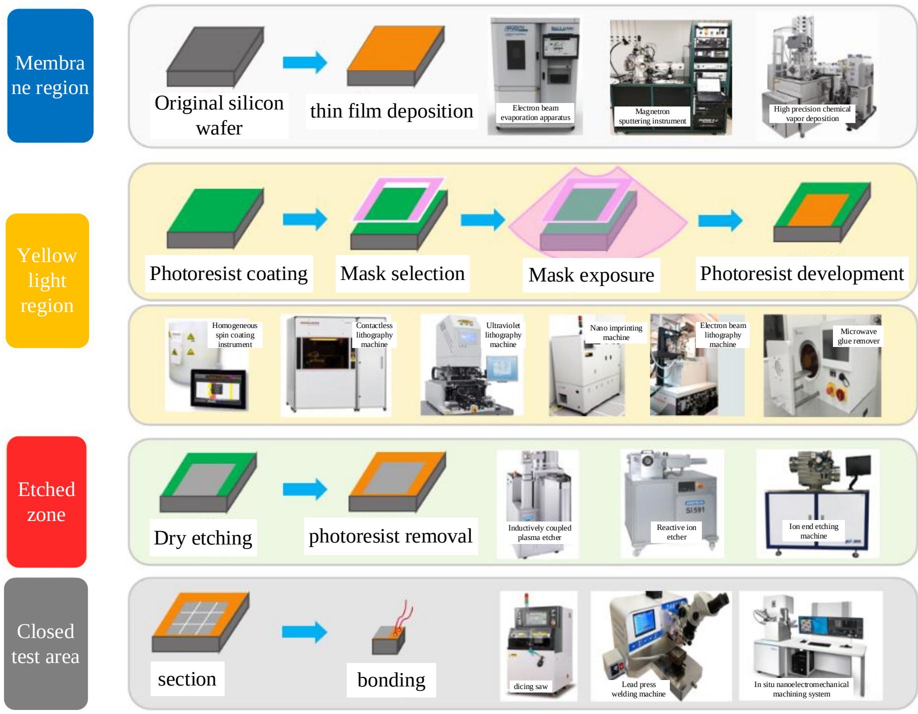


Fig. 1. Schematic diagram of a micro-nano embedded system.

Micro-nano embedded systems have the following characteristics (as shown in Fig. 2): 1) miniaturization; 2) low power consumption; 3) high performance; 4) multifunctionality; 5) integration; 6) intelligence; 7) formulatability; 8) real-time; 9) reliability; and 10) ease of portability [17]. Micro-nano embedded systems have a wide range of applications in several fields due to the above advantageous features, including smartphones, wearable devices, Internet of Things, healthcare, energy and environmental protection, national security and defense, etc. [18], as shown in Fig. 3.

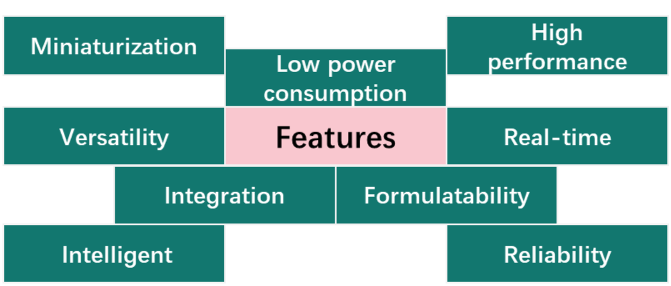


Fig. 2. Characteristics of micro-nano embedded systems.

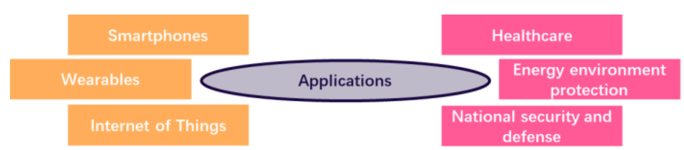


Fig. 3. Micro-Nano embedded system application.

2) In-depth development process of micro- and nano-embedded systems: The in-depth development of micro- and nano-embedded systems is a complex process involving close collaboration between hardware and software [19], and the key steps of the process (see Fig. 4) are as follows:

- Requirements analysis. Before development, it is necessary to carefully analyze and clarify the requirements of the micro-nano embedded system, including functional requirements, performance indicators,
- System design. Based on the hardware platforms, software architecture and so on.results of the micro- and nano-embedded system requirements analysis, system

design is carried out to select the appropriate hardware platform and software architecture, define the modules and interfaces of the system, as well as to develop the system testing and validation plan.

- Hardware design. Select and configure the processor, memory, sensors, communication interfaces, etc.
- Software development. Realize the function and control logic of the system, i.e., write the underlying driver, customization of the operating system, implementation of algorithms, etc.
- Integration and Testing. Integrate hardware and software components into a complete system for system-level functional and performance testing.
- Optimization and debugging. Optimize and debug the system to ensure that it meets the performance requirements and has good stability and reliability.
- Deployment and Maintenance. Complete the deployment of the developed embedded system to the target device or system and perform maintenance and support.

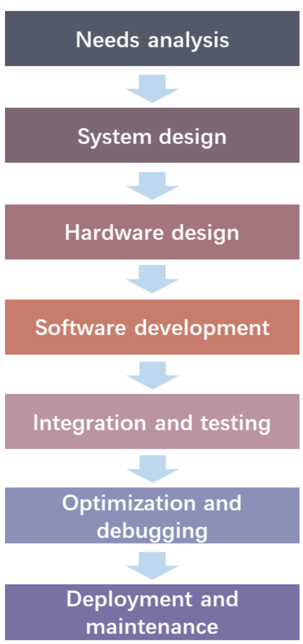


Fig. 4. Development process of micro-nano embedded system.

3) Framework of test and analysis system for in-depth development of micro- and nano-embedded systems: In the process of deep development of micro-nano embedded system, the integration test of hardware and software as well as optimization debugging as an important part of the system development can help designers to find and solve the potential problems and defects of micro-nano embedded system [19]. In order to help developers of micro-nano embedded system design management, improve the efficiency of micro-nano embedded system in-depth development, and increase the prediction accuracy of development test analysis, this paper combines intelligent optimization algorithms and integrated learning algorithms to study the optimization model of micro-nano embedded system in-depth development test, and therefore designs an intelligent test analysis framework for the in-depth development of micro-nano embedded system based on intelligent optimization algorithms to improve the integrated learning technology (see Fig. 5).

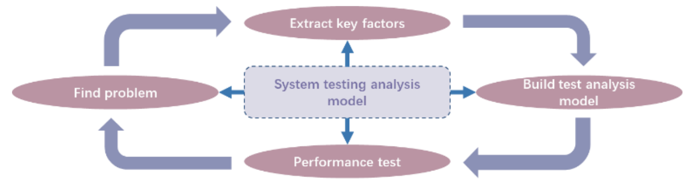


Fig. 5. Intelligent test and analysis framework for the development of micro and nano embedded systems.

B. Key Technical Content

According to the analysis framework, the research on intelligent test analysis method for deep development of micro-nano embedded system based on intelligent optimization algorithm to improve the integrated learning technology mainly includes four parts, including system development process analysis, system test analysis factor extraction, system test analysis data processing, and system development and test analysis model construction, as shown in Fig. 6.

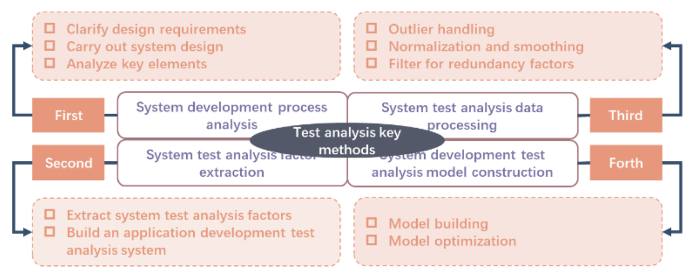


Fig. 6. Key technologies for intelligent test and analysis of micro and nano embedded system development.

1) Analysis of the system development process: The system development process analysis is mainly to clarify the micro-nano embedded system design requirements, carry out the system design, and analyze the key elements of the in-depth development process of micro-nano embedded system.

2) Extraction of factors for systematic test analysis: According to the principles of systemic, holistic, and process, the system test analysis factors are extracted from the key elements of the in-depth development process of micro- and nanoembedded systems, and the application development test analysis system is constructed.

3) System test and analysis data processing: Extract the system test analysis factor data from the test data, and then annotated to construct the data set, for the abnormal values and outliers, the use of proximity to take the value of the correction data, for the vacant value of the random forest model to fill in the prediction method, and after that the data normalization and smoothing, through the Pearson correlation coefficient method of filtering the redundant factors, to get the input data matrix, as shown in Fig. 7.

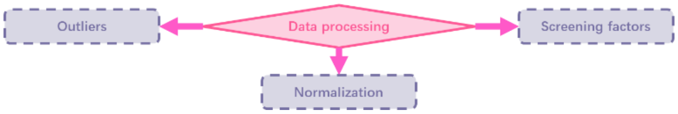


Fig. 7. Data processing.

4) System development test analysis model construction: Taking the labeled data matrix as input and the test analysis values as output, the lightweight gradient boosting machine is used to construct a test analysis model for the development of micro-nano embedded systems; at the same time, the photon search algorithm is used to optimize the test analysis model for the development of micro-nano embedded systems based on the lightweight gradient boosting machine algorithm, and the specific constructive optimization paradigm is shown in Fig. 8.

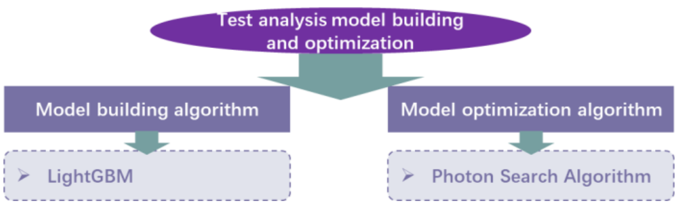


Fig. 8. Optimization paradigm for building test and analysis models for development of micro and nano embedded systems.

III. Application Analysis Modeling and Optimization for Micro-Nano Embedded System Development

A. LightGBM Algorithm

Lightweight Gradient Boosting Machine (LightGBM) [20] is a gradient boosting tree-based boosting method in integrated learning, which was proposed by Microsoft in 2017, and is currently one of the best-performing boosting methods. While the traditional GBDT method greatly increases the computational complexity and memory usage of the model when the amount of sample data and features grows, LightGBM accelerates the model training speed without affecting the model accuracy [21].

In order to reduce the amount of training data, LightGBM adopts the gradient one-sided sampling algorithm, which gives different sampling weights to the data according to the gradient values, retains the data with large gradients (i.e., not yet trained, which contributes more to the improvement of the information gain), and randomly samples the data with small gradients and maintains the original distribution of the data, as shown in Fig. 9. This sampling method results in more accurate information gain compared to uniform random sampling. In order to reduce the sample features during training, LightGBM uses an independent feature merging algorithm to bind mutually exclusive features (several features that are not zero at the same time, e.g., unique heat coding) from high-dimensional features together to form a single feature, thus reducing the feature dimension and improving the training speed without affecting the accuracy.

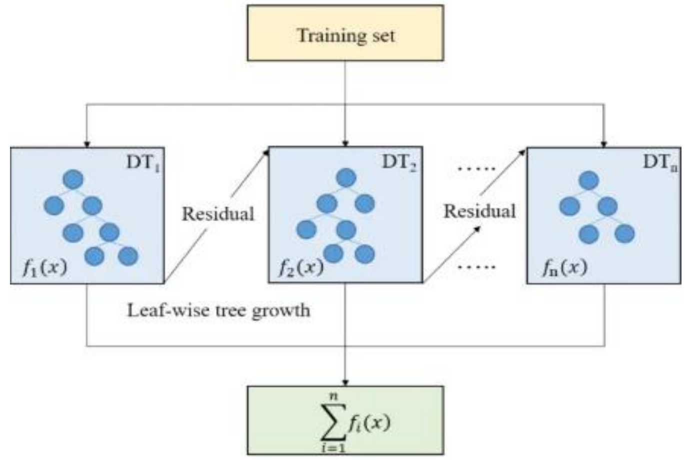


Fig. 9. Structure of LightGBM algorithm.

The LightGBM initial model objective function consists of a loss function with regularization:

$$O_{bj} \approx \sum_{i=1}^{I} Loss\left(y_i, \hat{y}_i\right) + \sum_{t=1}^{T} \Omega\left(f_t\right) \tag{1}$$

where, O_{bj} denotes the objective function, $Loss$ is the loss function, $\Omega\left(f_t\right)$ is the regularization term, I is the tree depth, y_i is the true value, $\hat{y}_i$ is the predicted value, T is the number of cotyledons, and f_t is the tth generation prediction function.

A second-order Taylor expansion is performed on the objective function determined from the tth generation prediction results:

$$O_{bj} \approx \sum_{i=1}^{n}\left[Loss\left(y_i, \hat{y}_i^{t-1}\right) + g_i f_i\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right)\right] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{2}$$

where, $f_t\left(x_i\right)$ denotes the new prediction function when the model is iterated, g_i is the first-order derivative of Loss, h_i is the second-order derivative of Loss, γ is the new node complexity cost parameter, and w_j is the leaf node value, λ indicates the leaf node value coefficient.

Accumulate the first-order and second-order gradients, and then make the first-order derivative of the objective function with respect to w_j is 0, i.e., take the extreme point:

$$O_{bj}^{t} \approx -\frac{1}{2} \sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \gamma T \tag{3}$$

where, G_j denotes the first order gradient accumulation value and H_j denotes the second order gradient accumulation value, λ denotes the complexity cost parameter of the new node.

The optimal tree is the one that minimizes the value of the objective function among the different arrangement structures. Use the splitting gain formula G_{ain} to evaluate whether to split leaf nodes or not. If $G_{ain} > 0$, continue splitting to improve the model performance, otherwise stop splitting. After repeated iterations, the LightGBM strong learner algorithm model is finally obtained.

LightGBM has the following features (Fig. 10): 1) histogram-based decision-making algorithm (Fig. 11) improves computational speed and reduces memory usage; 2) adopts a leaf growth strategy, which helps to improve model accuracy; 3) one-sided gradient sampling accelerates learning and reduces computational complexity; 4) mutual exclusion feature bundling reduces the number of features and improves computational efficiency; 5) supports parallel and distributed learning; 6) Cache optimization accelerates the data exchange speed; 7) Supports a variety of loss functions to meet different business needs; 8) Regularization and pruning strategies control the model complexity and prevent overfitting; 9) The algorithm has good model interpretability [22].

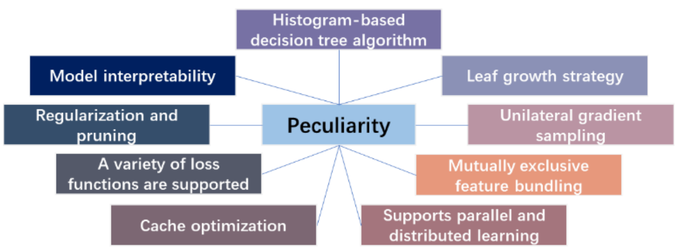


Fig. 10. Characteristics of LightGBM algorithm.

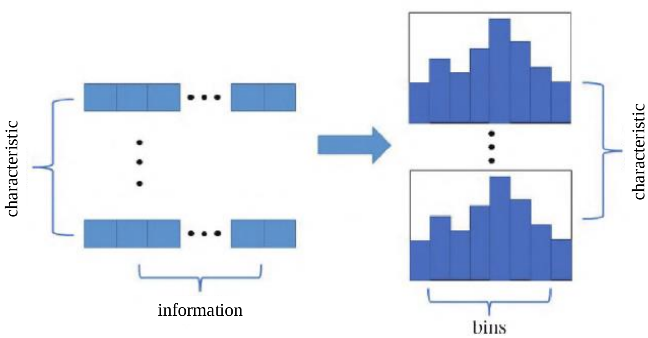


Fig. 11. Histogram based decision making algorithm.

LightGBM is widely used in binary classification, multiclassification, and sorting scenarios, for example, in personalized product recommendation, risk management, and market analysis. It can handle a large number of features and samples and is suitable for industrial-grade data analysis and complex machine learning tasks [23].

B. Photon Search Algorithm

Photon Search Algorithm (PSA) [24] is a heuristic algorithm based on physical phenomena proposed in 2019. The theoretical basis of the algorithm is derived from the photon hypothesis and quantum theory proposed by physicists Max Planck, Einstein and Broglie. The photon search algorithm has been studied for its strong global exploration ability and high search efficiency, but it underperforms in local exploitation ability and has low convergence accuracy.

1) Optimization principle: The working principle of the photon search algorithm involves the initialization of the photon's motion, the observation behavior and the search exclusion principle. In the algorithm, the position of the photon is updated taking into account the distance to the global best fitness value photon and the distance passed by the photon in the iteration. In addition, the algorithm designs the observation behavior to model the quantum uncertainty principle and the search exclusion principle based on the bubbleley incompatibility principle to avoid photons occupying the same position [25].

In the PSA algorithm, each photon represents a search agent that aims at the optimal solution, obtains a fixed speed, goes through iterations, and outputs the optimal solution.

The specific optimization strategies are as follows:

a) Photon motion

Define photonic individual:

$$X_i = \left(x_i^1, \cdots, x_i^d, \cdots, x_i^n\right), i = 1, 2, \cdots, N \quad (4)$$

where X_i denotes the ith photon, and x_i^d denotes the dth dimension of photon i.

The mathematical model of photon optimized motion is as follows:

$$x_i^d\left(t+1\right) = x_i^d\left(t\right) + De \cdot v_i^d\left(t+1\right) \quad (5)$$

$$v_i^d\left(t+1\right) = \frac{R_{Len}}{R_{ig}}\left(x_g^d\left(t\right) - x_i^d\left(t\right)\right) \quad (6)$$

$$R_{Len} = Scl \cdot \left\| X_{upper} - X_{lower} \right\|_2 \quad (7)$$

$$R_{ig} = \left\| X_i\left(t\right), X_g\left(t\right) \right\|_2 \quad (8)$$

$$De = \frac{ext}{t} \quad (9)$$

where, $x_i^d\left(t\right)$ denotes the d-dimensional position information of the i^{th} photon in the t^{th} iteration, $v_i^d\left(t+1\right)$ denotes the velocity information of the i^{th} photon in the d-dimension in the $t+1^{th}$ iteration, De is the convergence weight, which is used to adjust the convergence speed in the search process, R_{Len} denotes the distance passed by the photon in the photon iteration, R_{ig} denotes the Euclidean distance between the ith photon and the current optimal photon, $x_g^d(t)$ is the d-dimensional position information of the optimal photon in the tth iteration, Scl denotes the value of the weight, and ext is the convergence coefficient.

b) Observation of behavior: In order to simulate the photon uncertainty principle, the observation behavior is designed to calculate the photon position:

$$x_i^d(t) = x_i^d(t) + De \cdot randA \tag{10}$$

Where $randA$ denotes a random number between -1 and 1.

c) Search exclusion principle: In the PSA algorithm, based on the principle of bubbly incompatibility, the search exclusion principle behavior is used to update the photon individual positions as follows:

$$x_i^d = x_{low}^d + \left(x_{up}^d - x_{low}^d\right) \cdot randB \tag{11}$$

where x_{low}^d and x_{up}^d denote the lower and upper bound ranges of the dth dimension, respectively, and $randB$ denotes a random number between 0 and 1.

2) Process steps: According to the above PSA algorithm behavior description, the PSA algorithm flow is shown in Fig. 12 with the following steps:

- Step 1: Initialize the position of the photon X_i ;
- Step 2: Calculate the photon fitness value and calculate the distance passed in the photon iteration R_{Len} ;
- Step 3: Update R_{ig} , the velocity and position of the photon, and update the photon using the observation behavior;
- Step 4: Calculate the photon fitness value and update the global optimal photon;
- Step 5: If t<Max_T, return to step 3, otherwise go to step 6;
- Step 6: The algorithm terminates and outputs the optimal solution.

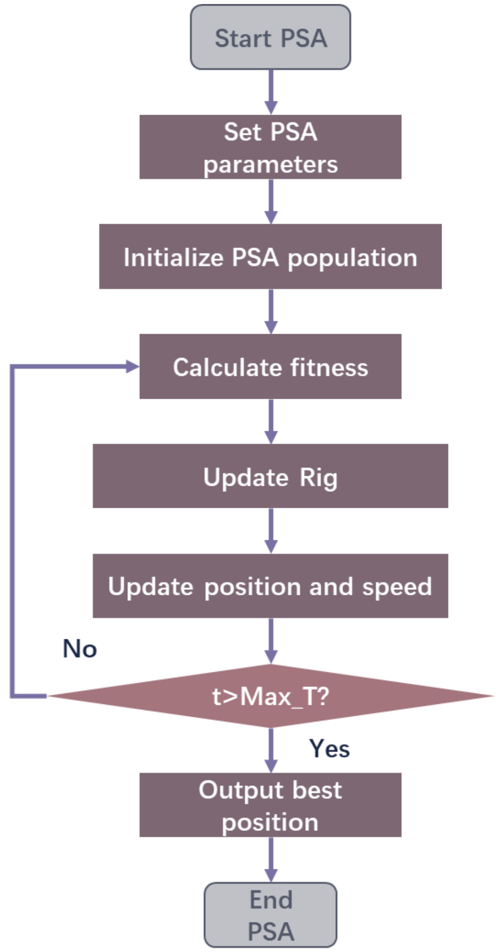


Fig. 12. Flowchart of PSA algorithm.

C. PSA-LightGBM Model Application

1) PSA-LightGBM: In this paper, we use real number coding to encode the number of cotyledons, tree depth, learning rate and minimum data number of LightGBM algorithm, and the dimensions of photon individuals are 4-dimensional, as shown in Fig. 13. Each photon individual includes the dimensions of the number of cotyledons L, the tree depth D, the learning rate l and the minimum data number S.

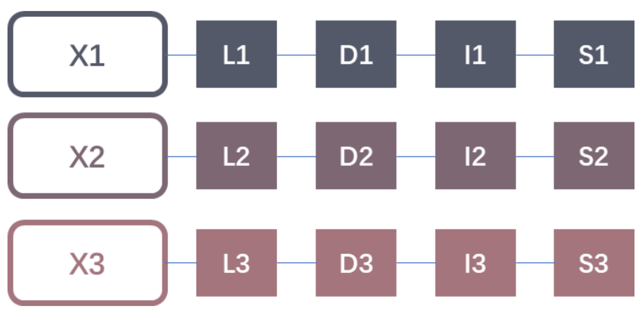


Fig. 13. PSA-LightGBM algorithm coding method.

Analyzing the application analysis problem of integrated development of micro and nano embedded systems, the problem can be considered as a predictive regression problem, so, RMSE is used as the fitness value in the PSA-LightGBM model.

According to the coding method and the fitness function, the steps of LightGBM application analysis method based on PSA algorithm (shown in Fig. 14) are as follows: 1) take the number of cotyledons L, the tree depth D, the learning rate l and the minimum number of data S as the optimization objects in the LightGBM model; 2) set the optimization parameter range of the PSA algorithm, the size of the population, and the maximum number of iterations, and initialize the population of the PSA algorithm ; 3) Calculate the fitness value based on RMSE; 4) Update the photon individual positions and velocities based on LightGBM parameters, and output the optimal parameter set to LightGBM; 5) Establish the PSA-LightGBM model based on the optimal parameter combination.

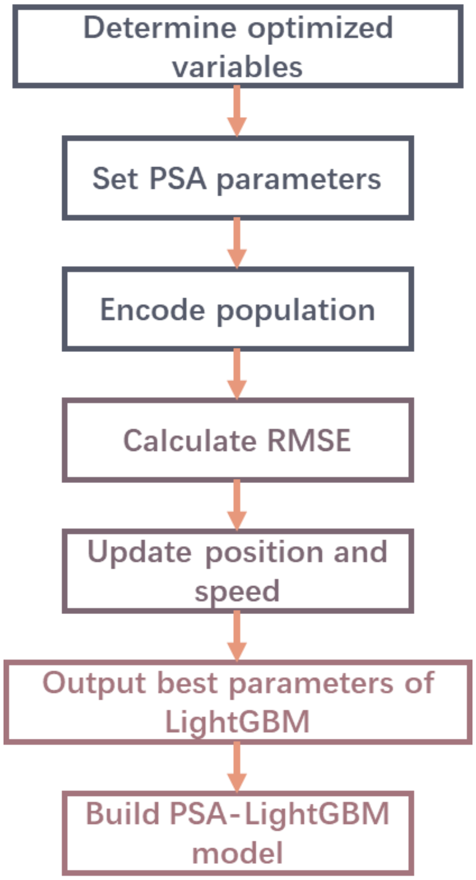


Fig. 14. PSA-LightGBM.

2) Algorithm application: In order to construct an application analysis model for the development of micro-nano embedded systems, this paper applies the PSA-LightGBM model to the in-depth development problem of micro-nano embedded systems under the complex integration architecture, and the specific application flow is shown in Fig. 15. The application of PSA-LightGBM algorithm in the in-depth development problem of micro-nano embedded systems under the complex integration architecture is divided into the following flow:

a) Analyze the problem of in-depth development of micro-nano embedded system under complex integrated architecture, extract the analytical characteristic parameters of micro-nano embedded system development and application, and establish the analytical characteristic parameter set;

b) Collect data related to analytical features during the in-depth development of micro-nano embedded systems in complex integrated architectures and use appropriate data processing techniques to obtain normalized dimensionality-reduced datasets;

c) Combine PSA-LightGBM algorithm to construct the mapping relationship between the development application analysis feature parameter values and the development application analysis scores, the specific PSA-LightGBM algorithm application analysis schematic is shown in Fig. 16.

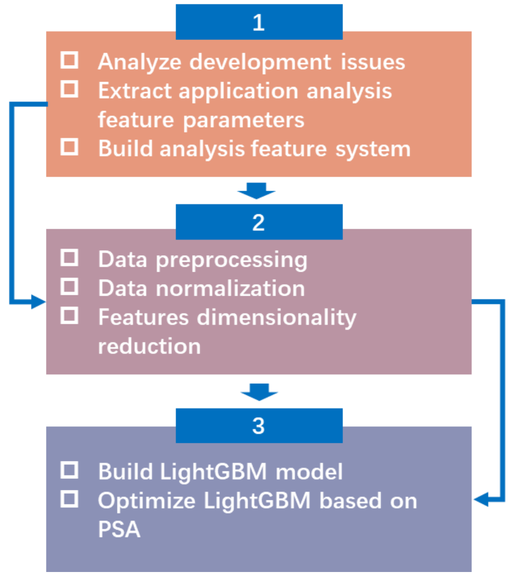


Fig. 15. Application flow of PSA-LightGBM algorithm.

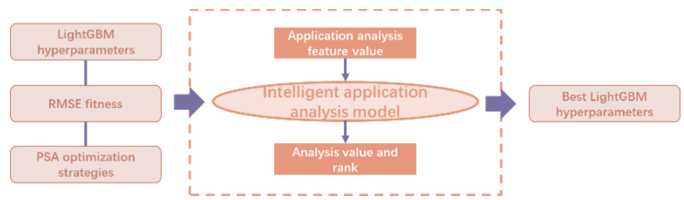


Fig. 16. PSA-LightGBM algorithm application analysis.

IV. Simulation and Analysis

A. Environmental Settings

This paper uses data from the in-depth development of micro-nano embedded systems under a complex integrated architecture. A total of 3530 data sets are used, with 80% of the data used as the training set for the application analysis model, 10% of the data used as the validation set during the optimisation process, and 10% of the data set used as the test set.

Software environment: programming environment Python 3.8, visualisation software Matlab 2022a, operating system Wins10.

The comparison algorithms include LightGBM, GWO-LightGBM, HHO-LightGBM, TLBO-LightGBM and PSA-LightGBM. The population size of the GWO, HHO, TLBO and PSA algorithms is set to 50, and the maximum number of iterations is 1000 and other parameter settings are shown in Table I.

TABLE I. Application Development Analysis Model Parameter Settings

No.	Algorithms	Settings
1	LightGBM	L=30, I=0.1, S=20
2	GWO- LightGBM	a=[-2,2]
3	HHO-LightGBM	E_0=2
4	TLBO-LightGBM	Teaching factor=1.2
5	PSA-LightGBM	No

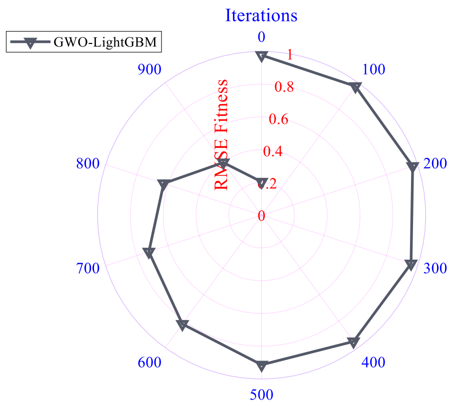
The range of GWO, HHO, TLBO, and PSA algorithms to optimize the LightGBM parameters number of cotyledons L, tree depth D, and learning rate l with minimum number of data S is shown in Table II.

TABLE II. OPTIMIZED PARAMETER RANGE SETTING

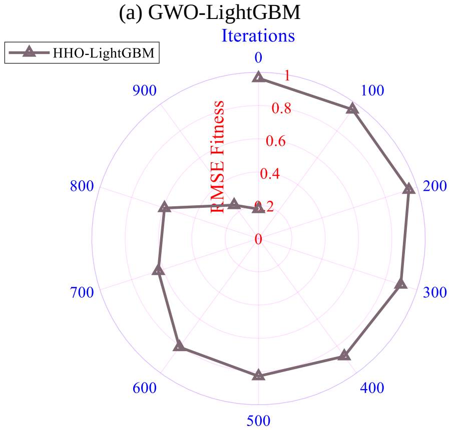
No.	Hyperparameters	Var.	Range
1	The number of cotyledons	L	[20,100]
2	The depth of the tree	D	[3,8]
3	The learning rate	L	[0.01, 0.3]
4	Minimum number of data	S	[1,30]

B. Analysis of Results

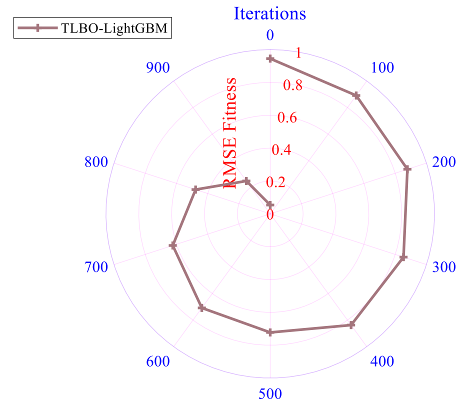
In order to further improve the performance of the analytical model for the development and application of micro- and nanoembedded systems, the PSA algorithm is used to find the optimal set of parameters by taking the number of cotyledons L, the depth of the tree D, and the learning rate l with the minimum number of data S as optimization parameters in the LightGBM model. In order to verify the validity set of PSA algorithm's excellent computational efficiency, GWO, HHO and TLBO are compared, and the change curve of each algorithm's adaptability is shown in Fig. 17 (a)-(d). From Fig. 17, it can be seen that the RMSE value of the PSA-LightGBM-based application analysis for the development of micro- and nanoembedded systems converges to the minimum value, and the GWO-LightGBM algorithm has the largest RMSE value, and PSA-LightGBM is better than the other algorithms.



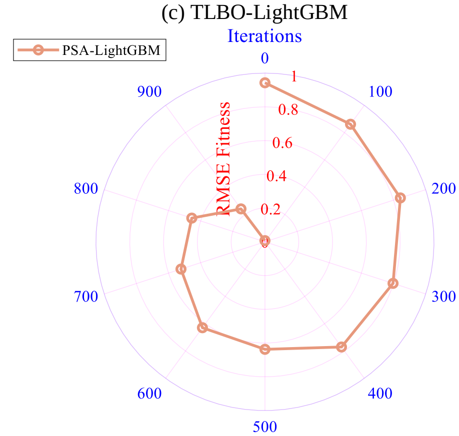
(a) GWO-LightGBM



(b) HHO-LightGBM



(c) TLBO-LightGBM



(d) PSA-LightGBM

Fig. 17. Comparison of the adaptation curves of the algorithms.

The hyperparameter optimization results of LightGBM model based on GWO, HHO, TLBO, and PSA algorithms are shown in Table III. From Table III, it can be seen that the optimal combination of parameters for PSA optimized LightGBM are: the number of mesocotyledons L=65, the tree depth D=5, the learning rate l=0.09 with the minimum number of data S=22.

TABLE III. RESULTS OF OPTIMIZING LIGHTGBM MODEL PARAMETERS BY EACH ALGORITHM

No.	Parameters	GWO	HHO	TLBO	PSA
1	The number of cotyledons	21	29	58	65
2	The depth of the tree	6	5	5	5
3	The learning rate	0.1	0.14	0.1	0.09
4	Minimum number of data	23	21	21	22

The predicted performance of development application analysis model based on LightGBM, GWO-LightGBM, HHO-LightGBM, TLBO-LightGBM, PSA-LightGBM algorithms for micro- and nanoembedded systems is analyzed using the test set. The results of the predicted performance of the development application analysis model based on each algorithm are shown in Fig. 18. From Fig. 18, it can be seen that the ME, MAE, MAPE, RMSE, and R2 values of PSA-LightGBM are 0.043, 1.012, 4.002, 0.477, and 0.99, respectively, and the prediction performance is better than LightGBM, GWO-LightGBM, HHO-LightGBM, and TLBO-LightGBM.

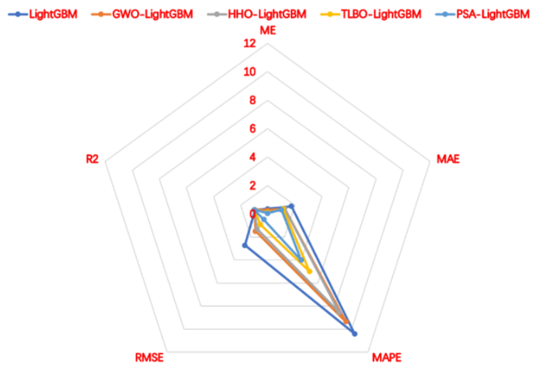


Fig. 18. Predictive performance statistics for each analytical model.

V. CONCLUSION

Focusing on the analysis of application development issues in the deep development of micro-nano embedded systems with complex integrated architectures, this paper proposes a development and application testing analysis method based on machine learning technology and intelligent optimisation algorithms, which achieves accurate prediction of system development and application testing. By analysing the deep development process of micro-nano embedded systems, a development and application testing analysis framework is designed, and the key technical content is introduced. For the problem of constructing an application testing analysis model, a development and application testing analysis method based on PSA-LightGBM is proposed by combining the LightGBM hyperparameter optimisation with the photonic search algorithm. Data analysis and verification show that compared with other algorithms, the PSA-LightGBM algorithm-based micro-nano embedded system development application test analysis method further reduces the test prediction error, and at the same time verifies the application feasibility of the development application test analysis method in the micro-nano embedded system deep development under the complex integrated architecture. The next step is to improve the PSA algorithm and improve the accuracy of the LightGBM model, and at the same time apply PSA-LightGBM and micro-nano embedded system development to other fields to verify the robustness and feasibility of the algorithm model.

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