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RESEARCH ARTICLE

Optimizing predictive accuracy in general medical exams using hybrid machine learning and metaheuristic optimization methods

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ABSTRACT

This study presents a hybrid, metaheuristic-driven optimization framework for power hyperparameter tuning in predictive modeling based on large-scale annual health examination data. Different from conventional grid and random search strategies, the proposed method directly incorporates particle swarm optimization, artificial bee colony, and gravitational search algorithm into the training pipeline of multiple machine learning models, enabling adaptive exploration of high-dimensional parameter spaces under clinical data constraints. The approach was evaluated on a comprehensive dataset comprising 93 clinical attributes and 1,000 patient records, with a specific focus on ischemic stroke risk prediction. Random Forest, decision tree, support vector machine, and logistic regression models were optimized using the proposed hybrid structure and benchmarked against baseline configurations. Experimental results demonstrate consistent and statistically significant reductions in mean squared error, mean absolute error, and root mean squared error, alongside improvements in R^2 and classification accuracy exceeding 99% for optimized logistic regression models, while maintaining computational efficiency suitable for routine clinical deployment. Beyond performance gains, the study introduces a stacked ensemble architecture guided by metaheuristic-tuned base learners, enhancing model robustness and generalization across training and independent test sets. These findings demonstrate the practical novelty of integrating swarm and numerical optimization into clinical predictive pipelines, providing a scalable and domain-agnostic solution for high-accuracy risk decision support in preventive healthcare and other data-intensive applications.

1. Introduction

In the realm of predictive analytics for healthcare, accurate forecasting of medical outcomes has become increasingly critical due to the growing volume and complexity of patient data. The study aims to enhance the precision of predictive models by integrating machine learning (ML) algorithms with metaheuristic optimization strategies. In particular, this method focuses on improving parameter selection for models applied to general medical examinations, leveraging powerful hybrid methods that combine the strengths

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of both domains. The study recently focused on trends in clinical follow-up and care-seeking behavior among patients diagnosed with ischemic stroke. A retrospective cohort design was used, drawing on data from the Japan Medical Data Center database.[1]

An innovative metaheuristic optimization algorithm was developed as part of the enterprise development (ED) process, which integrates tasks, organizational structure, technology, and interpersonal dynamics. This algorithm employs a switching activity approach to iteratively refine solutions during the search process.[Truong2024] Various metaheuristic strategies have been explored to enhance the performance of thermoelectric generators, with both single- and multi-objective optimization applied to improve power generation and efficiency.[3] In a subsequent phase, a simulation-based methodology was introduced to evaluate the performance of different metaheuristic techniques, including simulated annealing (SA), evolutionary algorithms (EA), and genetic algorithms (GA).[4] Metaheuristic optimization algorithms have gained significant traction due to their robust performance across a broad spectrum of optimization problems. Nevertheless, their application to real-world scenarios often presents challenges that demand comprehensive evaluation and refinement.[5]

Additionally, a multi-objective water resource optimization model, grounded in metaheuristic principles, was developed for the Manas River irrigation zone in Xinjiang, China.[6] Although the arithmetic optimization algorithm is conceptually simple and inspired by mathematical principles, this method has shown potential in addressing complex real-world problems. However, critical assessments have also highlighted common design limitations across many existing metaheuristics.[7] Many real-world optimization problems manifest as mixed-variable optimization problems, involving both continuous and discrete variables. A distinctive challenge of mixed-variable optimization problems lies in managing variable-size search spaces associated with dimensional variables.[8] In transportation planning, a multi-stage iterative framework was proposed, such as the high speed rail station location and alignment optimization framework, decomposing the problem into key subcomponents: identification of potential corridors, station placement, corridor sequencing, and collision-free alignment (both horizontal and vertical).[9]

A novel optimizer known as the newton-raphson-based optimizer (NRBO) was developed by integrating the trap avoidance operator and Newton–Raphson search rule, guided by matrix operations to enhance solution quality.[10] Further advancements in automated algorithm design were achieved through a flexible algorithmic architecture that supports automatic configuration and instantiation of metaheuristics.[11] In medical applications, especially breast cancer diagnostics, ML technologies have played a pivotal role in early detection. Feature selection techniques have proven essential in improving classification accuracy, reducing data dimensionality, and enhancing model interpretability.[12] In the context of fog computing, optimal fog device deployment is critical for ensuring network coverage and connectivity, both of which significantly affect quality of service. An efficient fog device deployment method was proposed to minimize computational and communication overhead while maximizing internal fog communication and edge device accessibility.[13] For balanced diabetic datasets, Particle swarm optimization (PSO) was employed, along with a genetic-based approach for selecting optimal architectures across multiple classifiers.[14]

Metaheuristics have been extensively utilized to address non-deterministic polynomial-hard problems in various domains. In network-on-chip architectures, these techniques help optimize performance parameters.[15] A comparative study of ten ML models, including AdaBoost, Bagging, CatBoost, and XGBoost, that highlighted the effectiveness of metaheuristic-assisted optimization.[16] For manufacturing applications, such as drilling microholes in glass epoxy composites, a combination of metaheuristic algorithms and central composite design techniques was used to enhance quality metrics like smoothness and deviation. The outcomes were further validated through Bayesian regularization-based ML models.[17] Despite their versatility, the stochastic nature of metaheuristic algorithms makes them problem-dependent, thereby limiting their applicability in certain scenarios.[18] Nevertheless, they remain a powerful tool for data mining, particularly in feature selection. Feature selection helps eliminate redundant variables while preserving those crucial for model performance. For example, the dingo optimization algorithm has been applied for FS on stock market datasets, demonstrating effective dimensionality reduction.[19]

To address challenges in high-dimensional optimization, a novel algorithm, quasirandom metaheuristic based on fractal search, was introduced. This method utilizes low-discrepancy sequences and fractal geometry to improve convergence.[20]

Table 1. Summary of the shortlisted annual healthcare dataset

ECG	Thyroid gland	Height	Weight	Vain	Blood pressure	I	E	Eyes
2	Tirads 1	165	60	78	130/80	A	B	A
2	Tirads 2	165	60	78	128/80	A	B	A
2	Tirads 2	75	64	90	135/74	A	B	A
2	Tirads 1	160	44.5	100	109/74	A	B	F
3	Tirads 1	168	68.8	98	140/85	A	B	A
2	Tirads 3	180	73	64	129/81	A	B	A
2	Tirads 3	161	65.3	63	160/89	A	B	A
2	Tirads 2	167	73	64	130/81	A	B	A
3	Tirads 1	177	65.3	63	110/89	A	B	A
2	Tirads 2	157	65.3	63	127/89	A	B	A

Notes: The dataset comprises 93 attributes and 1,000 records. Certain variables were coded to protect sensitive information. Abbreviations: A: No abnormal findings; B: Not detected; E: External department; ECG: Electrocardiogram; F: History of surgery.

Four other innovative algorithms, such as tyrannosaurus optimization algorithm, nutcracker optimization algorithm, golden eagle optimizer, and jellyfish search optimizer were designed for solving multi-objective problems.[21] In the context of university energy management, integrated artificial intelligence models, metaheuristics, and data augmentation were employed for accurate long-term energy usage forecasting.[22] For biotechnological applications, six ML models, including random forest, extreme gradient boosting, and kernel ridge regression, were used in conjunction with optimization techniques to improve lipase production predictions.[23] A novel metaheuristic, the tactical unit algorithm, was proposed to solve the optimal chiller loading problem, reducing energy consumption and carbon emissions in energy systems.[24]

The hiking optimization algorithm, inspired by hikers navigating rugged terrains, offers a new perspective on navigating optimization landscapes.[25] In thermal engineering, ultra-thin vapor chambers (UTVC) benefit from data-driven models that predict thermal resistance with high precision.[26] A topology-informed approach was developed to enhance PSO and SA using topological data analysis, guiding search processes via persistence diagrams and kernel density estimations.[27] Other studies also underscore the utility of metaheuristics in feature selection and optimization problems.[28,29] High-dimensional datasets often contain noisy or irrelevant features, which can degrade model performance. Metaheuristics such as ant colony optimization, PSO, and genetic algorithms effectively navigate complex search spaces to identify optimal feature subsets. One application of this approach involved optimizing Random Forest hyperparameters using PSO on the breast cancer dataset. The fitness function, employing five-fold cross-validation, evaluated combinations of max_depth and n_estimators over 20 iterations, identifying the configuration with the highest classification accuracy. Similarly, these techniques can be extended to other ML models such as support vector machine (SVM) XGBoost, and Neural Networks, with flexibility to incorporate various evaluation metrics (e.g., F1-score, area under the curve of the receiver operating characteristic curve) based on specific domain requirements.

For improved computational efficiency, parallel processing can be utilized, particularly for large-scale or complex models. An example of this approach was applied to a dataset derived from library patron interactions, as shown in Table 1. For improved computational efficiency, parallel processing can be utilized, particularly for large-scale or complex models. As a case study, we applied this strategy to the yearly health check dataset summarized in Table 1. In the industrial sector, a framework integrating deep learning and metaheuristic optimization was proposed for designing packed bed latent heat storage systems. The deep learning model, trained on data from validated computational fluid dynamics simulations, predicts system performance [30]. To address global optimization and engineering design challenges, the convex combination search algorithm was introduced. Built on the principles of linear convex combinations, the convex combination search algorithm balances exploration and exploitation with only two parameters: population size and number of generations. It has demonstrated robustness and effectiveness across

17 unconstrained multimodal and seven constrained benchmark problems.[31] In the domain of traffic safety, radar and lidar-based real-time speed detection systems have proven effective in enforcing speed limits, thereby reducing the risk of accidents.[32] Finally, the arctic puffin optimization algorithm, inspired by the behavioral ecology of puffins, combines underwater foraging (exploitation) with aerial exploration enhanced by Levy flight and velocity strategies. These mechanisms improve convergence rates and escape from local optima, making arctic puffin optimization a promising candidate for complex optimization tasks.[33–35]

The main focus of this study is an optimization problem, where features most strongly associated with ischemic stroke and its related risk factors are selected. PSO, GA, and gravitational search algorithm (GSA) are employed to identify the features most relevant to the targets. In the next step, the selected features are used to build a prediction model, which is then compared with a model based on the previous set of features to evaluate performance improvements. The best parameters are selected based on their effectiveness in handling numerical inputs.[36–41] These models are evaluated on their ability to predict outcomes using data obtained from annual medical examinations, optimizing performance metrics such as mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and R^2 score. With the increasing emphasis on annual health checkups as a preventive healthcare measure, optimizing the interpretation of health screening data has emerged as a pressing concern.

2. Fundamental definitions

Scikit-opt (also known as Sko) is a Python module that includes swarm intelligence algorithms, including artificial fish swarm, ant colony, immune, simulated annealing, genetic, and PSO. An algorithm for swarm optimization is called SwarmPackagePy. Each of the 14 optimization techniques included, such as the artificial bee algorithm, PSO, and GSA, can be applied to address specific optimization problems. The algorithms share a common set of parameters: N, function is the test function, lb and ub are the lower and upper bounds for the plot axes, dimension is the space dimension, and iteration is the number of iterations. Common methods across all algorithms include ge_agents(), which returns the history of all agents, and get_Gbest(), which returns the best position found by the algorithm.

Particle swarm optimization (PSO): As shown in Equation. 7, PSO is based on simulating the movement of particles in a search space, adjusting their positions based on personal and global best solutions.

Velocity update: The velocity of each particle v_i is updated based on the particle's previous velocity, the best position found by the particle itself, and the best position found by any particle in the swarm.

$$v_i(t+1) = wv_i(t)+c_1r_1(p_i-x_i(t))+c_2r_2(g-x_i(t)), \tag{1}$$

where $v_i(t)$ is the velocity of particle i at time step t, w is the inertia weight, c_1, c_2, are acceleration constants, r_1, r_2 are random values between 0 and 1, p_i is the best position of particle, g is the global best position found by the swarm.

Position update: The position of each particle is updated based on its velocity.

$$x_i(t+1) = x_i(t) + v_i(t+1), \tag{2}$$

where $x_i(t)$ is the position of particle i at time step t.

3. Artificial bee algorithm

As shown in Equation. 12, the ABC algorithm is an optimization algorithm inspired by the foraging behavior of honeybees. It is widely used for solving numerical and combinatorial optimization problems. The algorithm consists of three main phases: the employed bee phase, the onlooker bee phase, and the scout bee phase. In the employed bee phase, each bee searches for a new food source (solution) by modifying its current solution based on another randomly chosen solution. If the new solution is better, it replaces the old one; otherwise, the bee retains its current position. Next, in the onlooker bee phase, the onlooker bees evaluate the solutions found by the employed bees and select promising ones based on a probability proportional to their quality. They then perform local searches to refine the selected solutions. Finally, in the scout bee phase, if a solution does not improve after a certain number of iterations, it is abandoned, and the scout bees randomly generate a new solution to explore other potential areas in the search space.

A population of N food sources (solutions) is randomly generated in the search space:

$$X_{i,j} = X_{min,j} + rand(0,1) \times (X_{max,j} - X_{min,j}), \tag{3}$$

where X_{ij} is the position of the i^{th} food source in the i^{th} dimension. $X_{min,j}$ and $X_{max,j}$ are the lower and upper bounds of the search space. $rand(0,1)$ is a random number between 0 and 1.

Each employed bee searches for a new food source near its current position by updating its position as:

$$V_{i,j} = X_{i,j} + \phi_{i,j} \times (X_{i,j} - X_{k,j}), \tag{4}$$

where $V_{i,j}$ is the new candidate solution, $X_{i,j}$ is the current food source position, and $X_{k,j}$ is a randomly generated number in the range $[-1, 1]$. If the new solution $V_{i,j}$ has a better fitness value than the old one, it replaces $X_{i,j}$.

The probability of selecting a food source is determined by its fitness:

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j}, \tag{5}$$

where P_i is the probability of selecting food source i, f_i is the fitness value of the i^{th} food source, and N is the number of food sources. The observers select food sources according to P_i and generate new solutions using the same formula as the bees employed.

If a food source is not improved for a certain number of cycles (limit parameter), it is abandoned, and a scout bee randomly generates a new food source:

$$X_{i,j} = X_{min,j} + rand(0,1) \times (X_{max,j} - X_{min,j}). \tag{6}$$

The algorithm iterates through these phases until a stopping condition is met, such as reaching the maximum number of iterations or finding a satisfactory solution.

3.1. Particle swarm optimization mathematical model

Let a swarm of N particles search in a d-dimensional space. The position and velocity of particle i at iteration t are denoted by $X_i(t) \in \mathbb{R}^d$ and $V_i(t) \in \mathbb{R}^d$, respectively.

Initialization:

$$X_i(0) \sim \mathcal{U}(X_{\min}, X_{\max}),$$
$$V_i(0) \sim \mathcal{U}(-V_{\max}, V_{\max})$$

$$Pbest_i(0) = X_i(0),$$
$$Gbest(0) = \arg\min_{Pbest_i(0)} f(Pbest_i(0))$$

Velocity and position update: For $t = 0, 1, \ldots, \text{Max\_Iter} - 1$:

$$V_i(t+1) = w(t)V_i(t) + c_1 r_1(t)\big(Pbest_i(t) - X_i(t)\big) + c_2 r_2(t)\big(Gbest(t) - X_i(t)\big)$$
$$X_i(t+1) = X_i(t) + V_i(t+1),$$

where $r_1(t), r_2(t) \sim \mathcal{U}(0,1)$.

Boundary constraint:

$$x_{ij}(t+1) = \begin{cases} X_{\min,j}, & x_{ij}(t+1) < X_{\min,j} \\ X_{\max,j}, & x_{ij}(t+1) > X_{\max,j} \\ x_{ij}(t+1), & \text{otherwise} \end{cases}$$

Fitness evaluation and best updates:

$$f_i(t+1) = f\big(X_i(t+1)\big)$$

$$Pbest_i(t+1) = \begin{cases} X_i(t+1), \\ f(X_i(t+1)) < f(Pbest_i(t)) \\ Pbest_i(t), \text{otherwise} \end{cases}$$

$$Gbest(t+1) = \arg\min_{Pbest_i(t+1)} f(Pbest_i(t+1))$$

Inertia weight update (optional):

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{\text{Max\_Iter}}\, t$$

Output:

$$Gbest^* = Gbest(\text{Max\_Iter}), \quad f^* = f(Gbest^*) \tag{7}$$

3.2. Artificial bee colony mathematical model

Let the population consist of N food sources (solutions) in a d-dimensional search space. Each solution is represented by

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{id}), \quad i = 1, 2, \ldots, N. \tag{8}$$

Initialization The initial population is generated randomly within the search bounds:

$$x_{ij} = X_{\min,j} + \text{rand}(0,1)\big(X_{\max,j} - X_{\min,j}\big),$$

where $\text{rand}(0,1)$ is a uniformly distributed random number.

The fitness of each solution is evaluated using the objective function:

$$f_i = f(X_i).$$

The initial global best solution is defined as:

$$Gbest = \arg\min_{X_i} f(X_i).$$

Employed bee phase: Each employed bee generates a new candidate solution in the neighborhood of its current solution:

$$v_{ij} = x_{ij} + \phi_{ij}\,(x_{ij} - x_{kj}), \quad k \neq i,$$

where $\phi_{ij} \sim \mathcal{U}(-1,1)$.

A greedy selection is applied:

$$X_i = \begin{cases} V_i, & f(V_i) < f(X_i), \\ X_i, & \text{otherwise.} \end{cases}$$

Onlooker bee phase: The probability of selecting a food source is computed as:

$$p_i = \frac{f_i}{\sum_{k=1}^{N} f_k}. \tag{9}$$

Onlooker bees select food sources based on p_i and generate new candidate solutions using the same neighborhood search equation as in the employed bee phase.

Scout bee phase: If a food source cannot be improved for a predefined limit of trials, it is abandoned and replaced by a new randomly generated solution:

$$x_{ij} = X_{\min,j} + \text{rand}(0,1)\big(X_{\max,j} - X_{\min,j}\big). \tag{10}$$

Global best update: After all phases, the global best solution is updated as:

$$Gbest = \arg\min_{X_i} f(X_i). \tag{11}$$

Termination: The algorithm iterates until the maximum number of iterations is reached or a convergence criterion is satisfied. The final output is:

$$Gbest^*, \quad f^* = f(Gbest^*). \tag{12}$$

3.3. Gravitational search algorithm mathematical model

Consider a system of N particles (agents) in a d-dimensional search space. The position of particle i at iteration t is given by

$$X_i(t) = \left(x_{i1}(t), x_{i2}(t), \ldots, x_{id}(t)\right). \tag{13}$$

initialization: Particles are initialized randomly within the search space:

$$x_{ij}(0) = X_{\min,j} + \text{rand}(0,1)\big(X_{\max,j} - X_{\min,j}\big).$$

The fitness of each particle is evaluated as:

$$f_i(t) = f\big(X_i(t)\big). \tag{14}$$

Mass calculation: Let $best(t)$ and $worst(t)$ denote the best and worst fitness values at iteration t. The mass of each particle is computed as:

$$m_i(t) = \frac{f_i(t) - worst(t)}{best(t) - worst(t)},$$

and normalized as:

$$M_i(t) = \frac{m_i(t)}{\sum_{k=1}^{N} m_k(t)}. \tag{15}$$

Gravitational constant update: The gravitational constant decreases over time:

$$G(t) = G_0 \exp\left(-\alpha \frac{t}{\text{Max\_Iter}}\right), \tag{16}$$

where G_0 is the initial gravitational constant and α is a control parameter.

Force computation: The force acting on particle i from particle j in dimension d is given by:

$$F_{ij}^d(t) = G(t)\frac{M_i(t)M_j(t)}{R_{ij}(t) + \varepsilon}\big(x_j^d(t) - x_i^d(t)\big), \tag{17}$$

where $R_{ij}(t) = \|X_j(t) - X_i(t)\|_2$ and ε is a small constant.

The total force on particle i is:

$$F_i^d(t) = \sum_{\substack{j=1 \\ j\neq i}}^{N} \text{rand}_j\, F_{ij}^d(t), \tag{18}$$

with $\text{rand}_j \sim \mathcal{U}(0,1)$.

Acceleration and velocity update: The acceleration of particle i is computed as:

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}. \tag{19}$$

The velocity update rule is:

$$v_i^d(t+1) = \text{rand}_i\, v_i^d(t) + a_i^d(t), \tag{20}$$

where $\text{rand}_i \sim \mathcal{U}(0,1)$.

Position update:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1). \tag{21}$$

Termination Steps are repeated until the stopping criterion is satisfied. The best solution is:

$$X^* = \arg\min_{X_i} f(X_i), \quad f^* = f(X^*). \tag{22}$$

4. Gravitational search algorithm

As shown in Equation. (22), the GSA is a nature-inspired optimization algorithm based on the principles of Newtonian gravity and mass interactions. It was introduced as a population-based metaheuristic algorithm where agents (solutions) are treated as objects with masses that interact with each other based on gravitational forces. The fundamental idea behind GSA is that each agent attracts others according to its fitness value, with better solutions having a stronger gravitational pull. Over time, agents move toward the best solutions due to the gravitational forces acting upon them.

In GSA, a set of agents is initialized randomly in the search space. Each agent's fitness value is evaluated using an objective function, and its mass is computed based on its relative fitness compared to the rest of the population. The gravitational force between agents determines their movement, with heavier (better) agents exerting stronger attraction on lighter agents. The velocity of each agent is updated based on the forces acting upon it, allowing solutions to explore and converge towards optimal values.

The key components of GSA include the gravitational constant (G), which decreases over time to balance exploration and exploitation, the force calculation, which determines the direction and intensity of an agent's movement, and the position update, which adjusts each agent's location

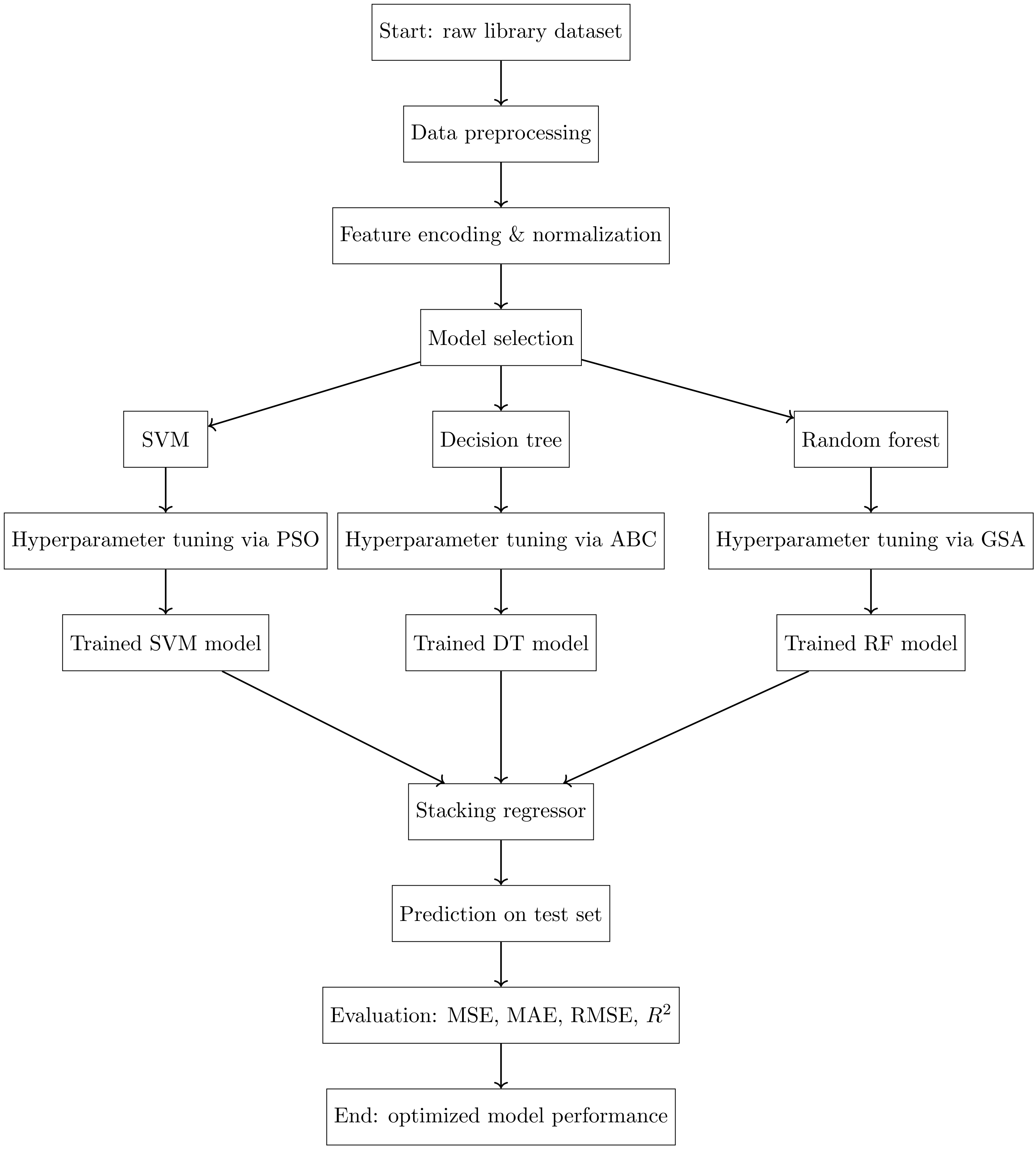

Figure 1. Processing steps for selecting parameters and prediction.

in the search space. By iterating through these steps, GSA enables efficient exploration and optimization. The algorithm has been successfully applied in ML, engineering design, and feature selection, proving a robust and adaptive optimization technique.

Additionally, GSA is a nature-inspired optimization algorithm based on Newton's Law of Gravity and Motion. It models a system where agents (candidate solutions) are treated as masses interacting with each other through gravitational attraction. A position vector represents each agent (solution) in an n-dimensional search space:

$$X_i = (x_i^1, x_i^2, \cdots, x_i^n), i = 1, 2, \cdots, N$$

where X_i represents the $i-th$ agent's position, N is the total number of agents, and n is the dimension of the search space.

5. Methodology

Metaheuristic optimization techniques have been widely applied to feature selection and classification tasks due to their ability to efficiently explore complex search spaces. Recent studies have demonstrated the effectiveness of combining metaheuristic algorithms with ML and deep learning models to enhance classification performance in various application domains. For example, deep learning-based metaheuristic optimization has been successfully employed for COVID-19 diagnosis using chest X-ray images, achieving improved classification accuracy and robustness[42] In addition, novel metaheuristic algorithms such as binary waterwheel plant optimization and dipper throated optimization have shown strong capability in selecting informative feature subsets, leading to enhanced predictive performance and reduced computational cost.[43,44] Furthermore, metaheuristic-based feature selection has been effectively applied in real-world forecasting systems, including wind speed prediction, where it significantly improved model accuracy and generalization.[45]

5.1. Data collection

Table 1 provides a detailed overview of the selected input attributes used in this study following metaheuristic-based feature selection. These attributes were chosen based on their relevance to predicting medical conditions derived from general health checkup data, with a focus on ischemic stroke and associated risk factors. The features are categorized into demographic, physiological, and behavioral groups, reflecting a multidimensional approach to clinical assessment. In addition to the structured datasets described earlier, the study also utilizes a comprehensive, shortlisted dataset derived from annual health care examinations. This dataset contains 93 attributes and 1,000 entries, providing a wide spectrum of clinical and diagnostic variables routinely collected during general medical screenings. The breadth of the dataset allows for in-depth analysis of correlations between different health indicators and the onset of conditions such as ischemic stroke. The inclusion of such diverse and granular data points contributes to the richness of the modeling process. The 93 attributes include demographic information, laboratory test results, imaging summaries, prior diagnoses, surgical histories, and subjective patient inputs, providing a comprehensive view a holistic view of an individual's health profile. This level of detail is particularly valuable for developing risk stratification models, especially for predicting silent or early-stage conditions such as ischemic stroke, which will not present overt symptoms in their early development.

5.2. Proposed methods

The proposed method follows a structured approach for selecting optimized parameters to enhance model performance. As illustrated in Figure 1, the process involves multiple stages, including data preprocessing, feature selection, model training, and parameter tuning using metaheuristic algorithms. Initially, raw data undergoes preprocessing to ensure consistency, where missing values are handled and feature scaling is applied. Next, feature selection techniques help in identifying the most relevant variables for model training, improving efficiency and accuracy. Following feature selection, machine learning models are trained using traditional algorithms such as SVM, DT, and random forest. These models serve as the foundation for prediction tasks. However, to further optimize their parameters, the study integrates metaheuristic optimization techniques such as PSO, ABC, and GSA. These techniques systematically explore the search space to fine-tune hyperparameters, maximizing model accuracy and minimizing error metrics such as MSE, MAE, and RMSE. Once the best-performing parameters are identified, the optimized models undergo validation using separate test datasets. The results are then compared against baseline models that do not employ metaheuristic optimization, demonstrating the effectiveness of the hybrid approach. This process ensures that the models generalize well to unseen data, making them robust for real-world applications.

6. Numerical results

6.1. Metrics evaluations

The mean_squared_error function computes a risk metric corresponding to the expected value of the squared logarithmic (quadratic) error or loss. If $\hat{y}_i$ is the predicted value of the i-th sample, and y_i is the corresponding true value, then the MSE estimated over $n_{samples}$ is defined as Equation. (23).

$$MSE(y, \hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}(log_e(1+y_i) - log_e(1+\hat{y}_i))^2, \quad (23)$$

where $log_e x$ is the natural logarithm of x. This metric is best to use when targets have exponential growth, such as population counts and average commodity sales over the years. This metric also penalizes an under-predicted estimate greater than an over-predicted estimate.

The mean_absolute_error, also known as mean absolute percentage deviation, is an evaluation metric for regression problems. The idea of this metric is to be sensitive to relative errors. It is for example not changed by a global scaling of the target variable. The formula is given by Equation. (24).

$$MAE(y, \hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}\frac{|y_i - \hat{y}_i|}{max(\epsilon, |y_i|)}, \quad (24)$$

where ϵ is an arbitrary small yet strictly positive number to avoid undefined results when y is zero.

The root_mean_squared_error function computes MSE, a risk metric corresponding to the expected value of the squared (quadratic) error or loss given by Equation. (25).

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2}, \quad (25)$$

The r2_score function computes the coefficient of determination, usually denoted as $\mathcal{R}^2$. It represents the proportion of variance (of y) that has been explained by the independent variables in the model. It provides an indication of goodness of fit and therefore a measure of how well unseen samples are likely to be predicted by the model, through the proportion of explained variance. Given by Equation. (26).

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n-1}(y_i - \bar{y})^2}, \quad (26)$$

where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n}, \sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}\epsilon_i^2$.

6.2. Result performance

Table 2 illustrates the accuracy using metaheuristic algorithms including PSO, ABC, GSA measured by MSE. MAE, RMSE, and R_2 score. The performance of the metaheuristic models was evaluated to attain the best parameters summarized in Table 3 with the values of C, degree, the leaf of maximum depth, and minimum samples. Using the new parameters, the new models are established and trained to show the new prediction. Using the parameters given on Table 3, we attain the accuracy of the new models, as shown in Table 4. Moreover, using the models, the new dataset was transformed to apply the best parameters. With the new parameters, the new prediction is transformed to training data set and the test set shown in Table 5. Table 6 presents the summary of parameters of the algorithms using

Figure 2 shows the combination of all fine-tuned and optimized models into a stacking regressor. Stacking regressor is an ensemble learning technique where multiple base models are trained, and their predictions are combined using a meta-model to improve overall performance. The meta-model learns how to best combine the outputs of the base models by using different regression models such as linear regression (LR), DT, random forest, and SVM. Fine-tuning of hyperparameters for each model was performed using metaheuristic algorithms such as PSO, GSA, and ABC. To investigate the behavior of the volatility of the optimized parameter, we performed the change of the values using SVM, DT, RF, and LR shown in Figures 3–6, respectively. The figures illustrate the change of the parameters upon the parameters C and degree in three-dimension by using different values in the annual healthcare checkup dataset.

We conducted an additional experiment using LR and DT models with numerical results derived from optimized metaheuristic parameters. The findings revealed a marked improvement in predictive performance for identifying "noikhoa" (ischemic stroke) cases within the annual healthcare dataset. The LR model was constructed using 60% of training, 20% for validation, and 20% for testing set. Using the best parameters obtained from the PSO, ABC, and GSA algorithms, the optimized models achieved higher accuracy, precision, and generalization compared to the baseline configuration. Specifically, the PSO-optimized LR model, with parameters C=23.3567 and max_iter=1,000, attained the highest accuracy of 0.9972, precision of 0.9976, recall of 0.9972, and F1-score of 0.9973 (Table 7). For max_depth=10 and min_samples_leaf=20, a DT model was constructed and is shown in Table 7. The ABC and GSA-based models also demonstrated strong and consistent results, both exceeding the baseline accuracy of 0.9967. As illustrated in Table 3, the optimized parameter tuning significantly reduced the error metrics while improving the coefficient of determination Figures 7 and 8. We also conducted an experiment for predicting ischemic stroke using logistic regression

Table 2. Predictive performance of models optimized with metaheuristic algorithms

	SVM			DT		
Algorithms	**PSO**	**ABA**	**GSA**	**PSO**	**ABA**	**GSA**
MSE	0.0093	0.0099	0.0096	0.0001	0.0823	0.0971
MAE	0.0938	0.0944	0.0942	0.0002	0.0123	0.1866
RMSE	0.0965	0.0996	0.0981	0.0002	0.2100	0.3116
R_2 score	0.9700	0.9680	0.9690	1.0000	0.1123	0.6881

Abbreviations: ABA: Artificial bee colony algorithm; DT: Decision tree; GSA: Gravitational search algorithm; MAE: Mean absolute error; MSE: Mean squared error; PSO: Particle swarm optimization; RF: Random forest; RMSE: Root mean squared error; SVM: Support vector machine.

Table 3. Best parameters obtained by each optimization algorithm

Optimizers	C	degree	max_depth	min_samples_leaf
PSO	23.3567	0.5868	10.2604	20.1570
ABA	1.0000	1.0000	22.8045	11.8170
GSA	20.2792	2.7429	32.7872	13.0280

Table 4. Evaluation metrics obtained for each algorithm

Optimizers	MSE	MAE	RMSE	R_2 Score
PSO	0.0095	0.0959	0.0978	0.9897
ABA	0.0095	0.0958	0.0977	0.9897
GSA	0.0085	0.0852	0.0924	0.9908

Abbreviations: ABA: Artificial bee colony algorithm; GSA: Gravitational search algorithm; MAE: Mean absolute error; MSE: Mean squared error; PSO: Particle swarm optimization; RF: Random forest; RMSE: Root mean squared error.

Table 5. Summary of support vector machine model predictions based on the best-performing parameters

Optimizers	MSE	MAE	RMSE	R_2 score
Evaluating on training set	0.0006	0.0005	0.0007	0.9999
Evaluating on test set	0.0005	0.0005	0.0007	0.9999

Abbreviations: MAE: Mean absolute error; MSE: Mean squared error;RMSE: Root mean squared error.

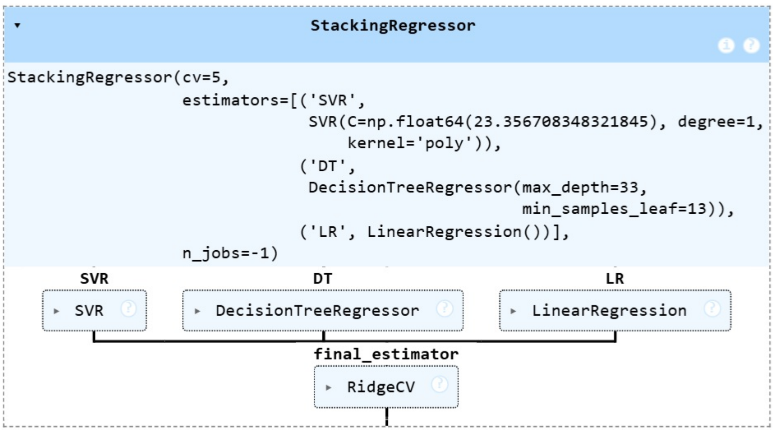

Figure 2. Integration of fine-tuned and optimized models into a stacking regressor for building optimal algorithms.

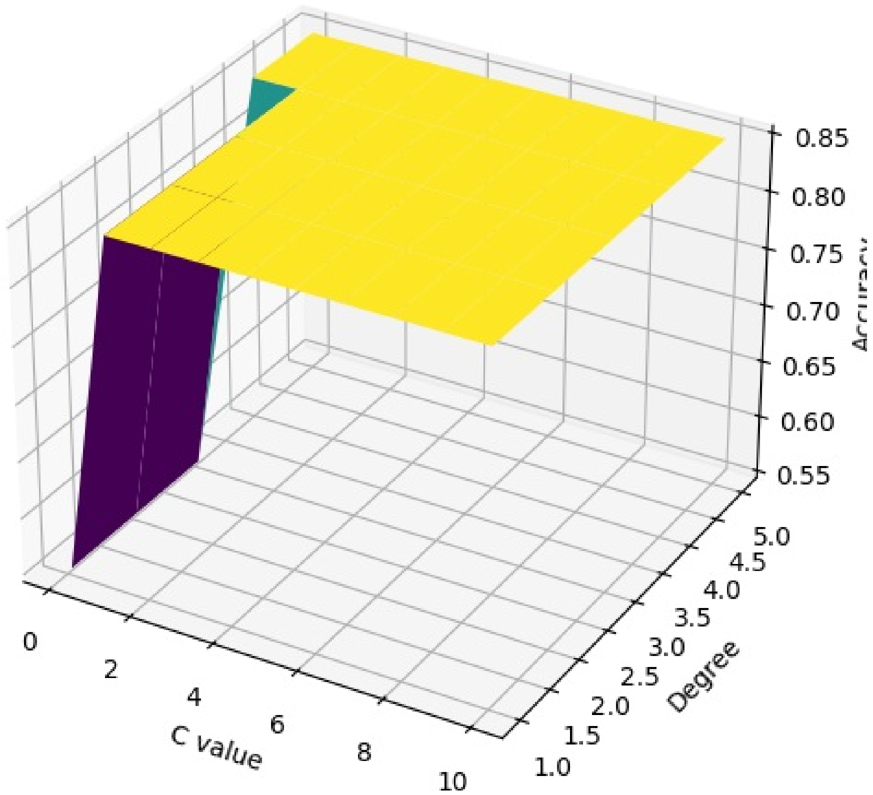

Figure 3. Support vector machine accuracy across varying values of C and degree.

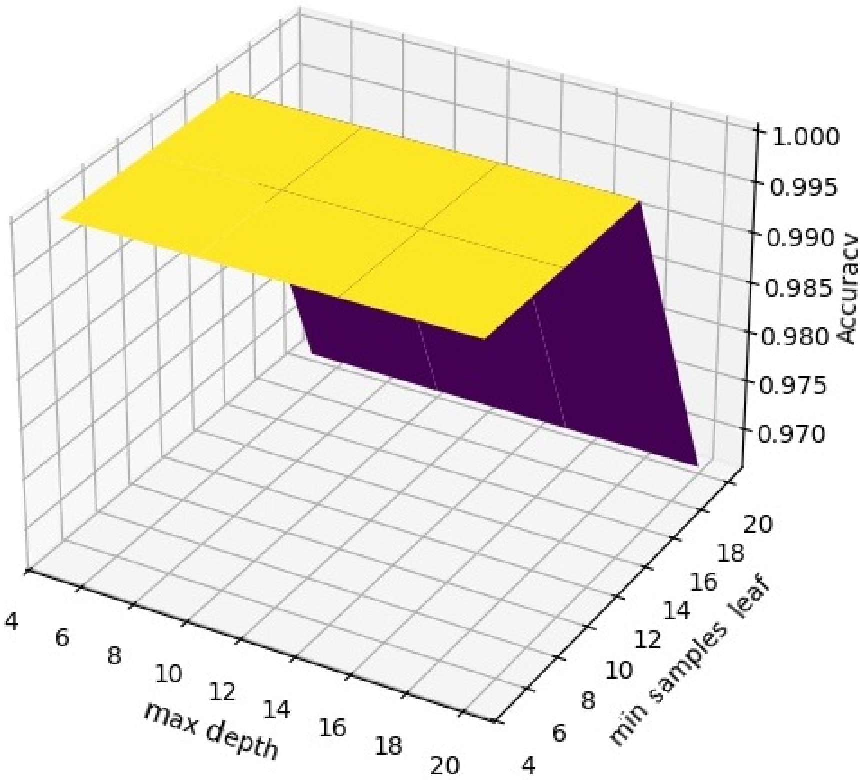

Figure 4. Decision tree accuracy across varying max_depth and min_samples_leaf values

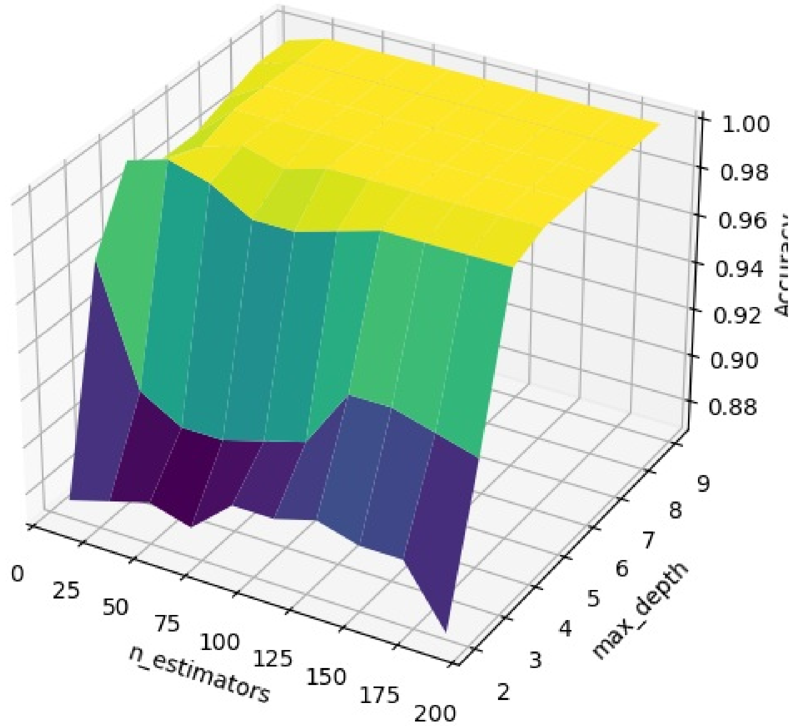

Figure 5. Random forest accuracy across different n$_{e}stimatorsandmax_{d}epthvalues.$

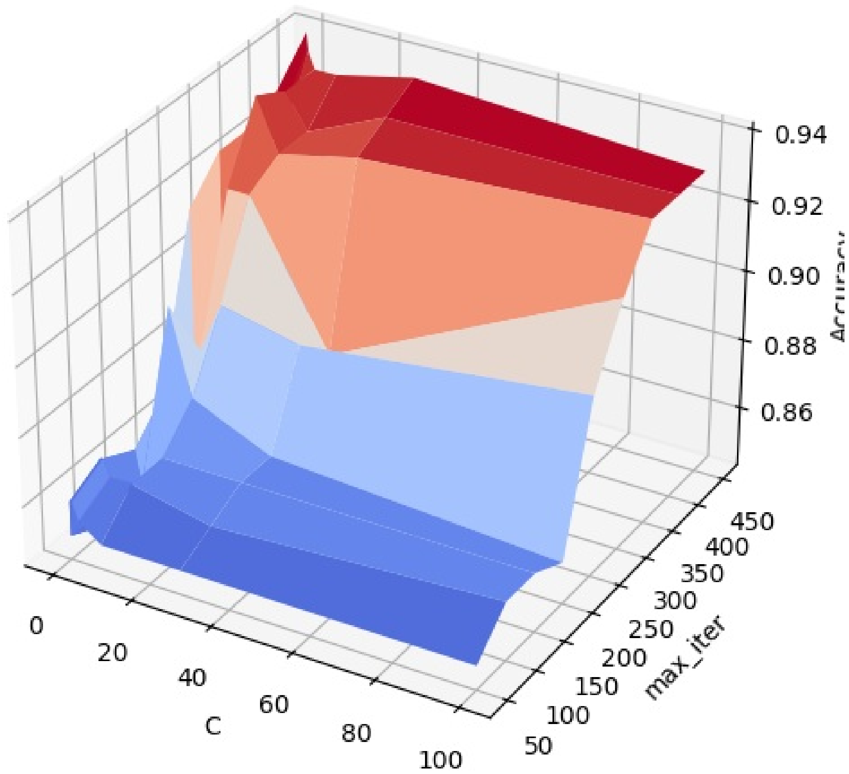

Figure 6. Logistic regression accuracy across different C and max$_{i}tervalues$

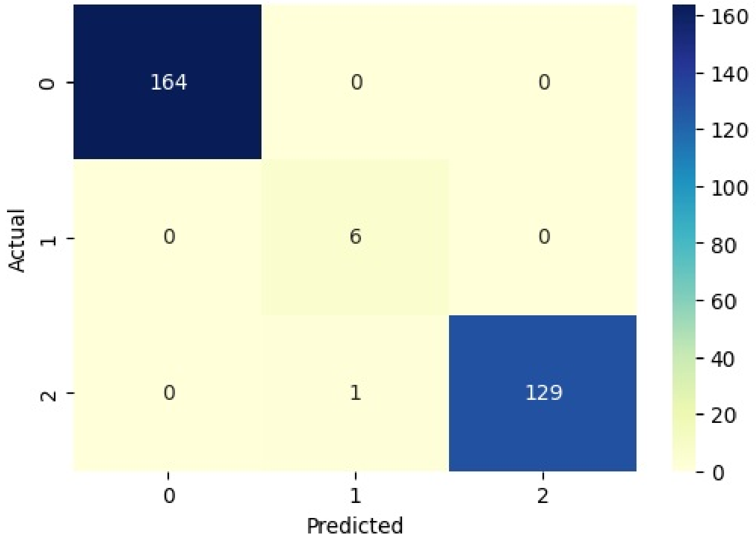

Figure 7. Logistic regression accuracy based on optimized algorithm parameters

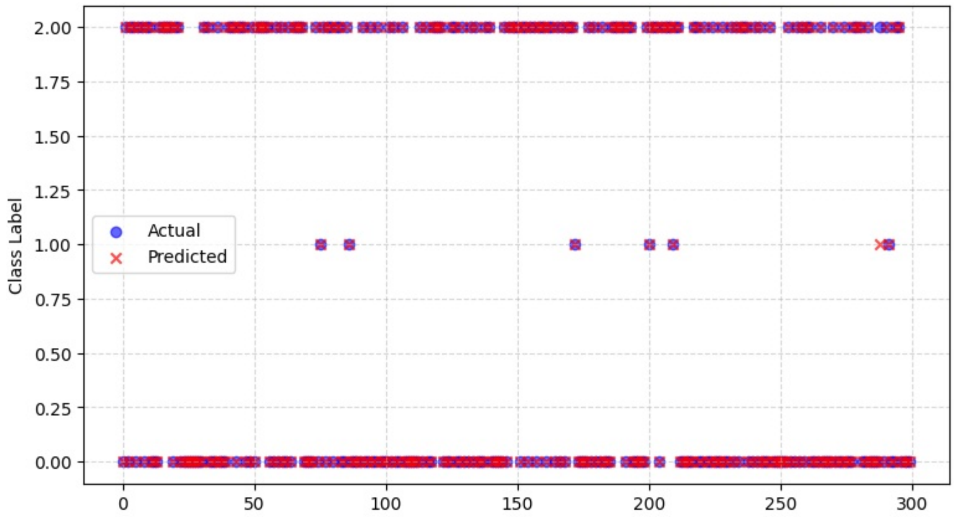

Figure 8. Logistic regression accuracy predicted with new parameters

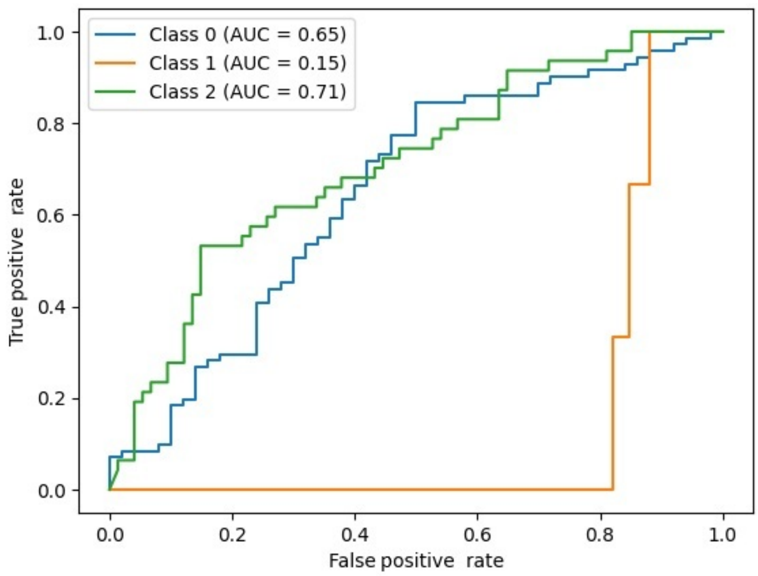

Figure 9. Receiver operating characteristic curve of the logistic regression model on the test set
Abbreviation: AUC: Area under the curve.

Table 6. Transparency and Reproducibility Summary for Metaheuristic Optimization

Aspect	**Particle swarm optimization**	**Genetic algorithm**
Search space (per feature)	Continuous binary mask $\in [0,1]$ for each feature dimension	Binary vector $\{0,1\}$ for each feature dimension
Hyperparameters searched	Inertia weight $w \in [0.5, 0.9]$; cognitive coefficient $c_1 \in [0.1, 2.0]$; social coefficient $c_2 \in [0.1, 2.0]$; number of particles $\in [20, 100]$	Population size $\in [20, 100]$; crossover probability $\in [0.6, 0.9]$; mutation probability $\in [0.01, 0.2]$; tournament size $\in [2, 5]$
Fitness/objective function	$J = \alpha(1 - \text{accuracy}) + (1 - \alpha)\left[1 - \frac{\text{selected features}}{total features}\right]$,	
$alpha = 0.5$	Classification accuracy of random forest on validation fold	
Model evaluated	Random forest classifier ($n\_estimators = 50$, random_state=42)	Random forest classifier ($n\_estimators = 50$, random_state=42)
Maximum iterations / generations	100 iterations	50 generations
Stopping criteria	Maximum iteration reached or no improvement in 10 iterations	Maximum generation reached or stagnation for Five generations
Cross-validation setup	Five-fold stratified cross-validation via pipeline including scaling, feature selection, and model training	Five-fold stratified cross-validation via pipeline including scaling, feature selection, and model training
Final evaluation	Independent held-out test set (30% of data), unseen during optimization	Independent held-out test set (30% of data), unseen during optimization

Table 7. Evaluation of logistic regression and decision tree for predicting ischemic stroke (”noikhoa”)

Models	**Accuracy**	**Precision**	**Recall**	**F1-score**
LR	0.9967	0.9971	0.9967	0.9968
DT	0.9801	0.9911	0.9932	0.9914

Abbreviations: DT: Decision tree; LR: Logistic regression.

with new parameters. The results of prediction are shown in Figures 6–8. Additionally, we evaluated the models on the test set and presented the ROC curves in Figures 9 and 10 for the LR and DT models, respectively. Furthermore, the near-identical performance between training and testing datasets confirms the stability and generalization capability of the models. These outcomes indicate that integrating metaheuristic optimization particularly the PSO approach substantially enhances the logistic regression model's ability to accurately detect ischemic stroke patterns from annual health checkup data, supporting the potential application in early diagnosis and clinical decision-making within internal medicine.

7. Limitations and discussion

The study identified optimal parameters using metaheuristic algorithms and improved predictive accuracy in ML models models. The discussion emphasizes the effectiveness of integrating ML models with metaheuristic optimization to achieve higher prediction performance. The experimental results confirm that metaheuristic-based approaches, such as PSO, ABC, and GSA, significantly improve parameter selection, thereby enhancing model performance. Additionally, the comparative analysis of various optimization techniques reveals that PSO consistently achieves the lowest MSE and RMSE, demonstrating its robustness in parameter tuning. Despite these advantages, the study acknowledges several challenges. The computational cost associated with running metaheuristic algorithms increases as the

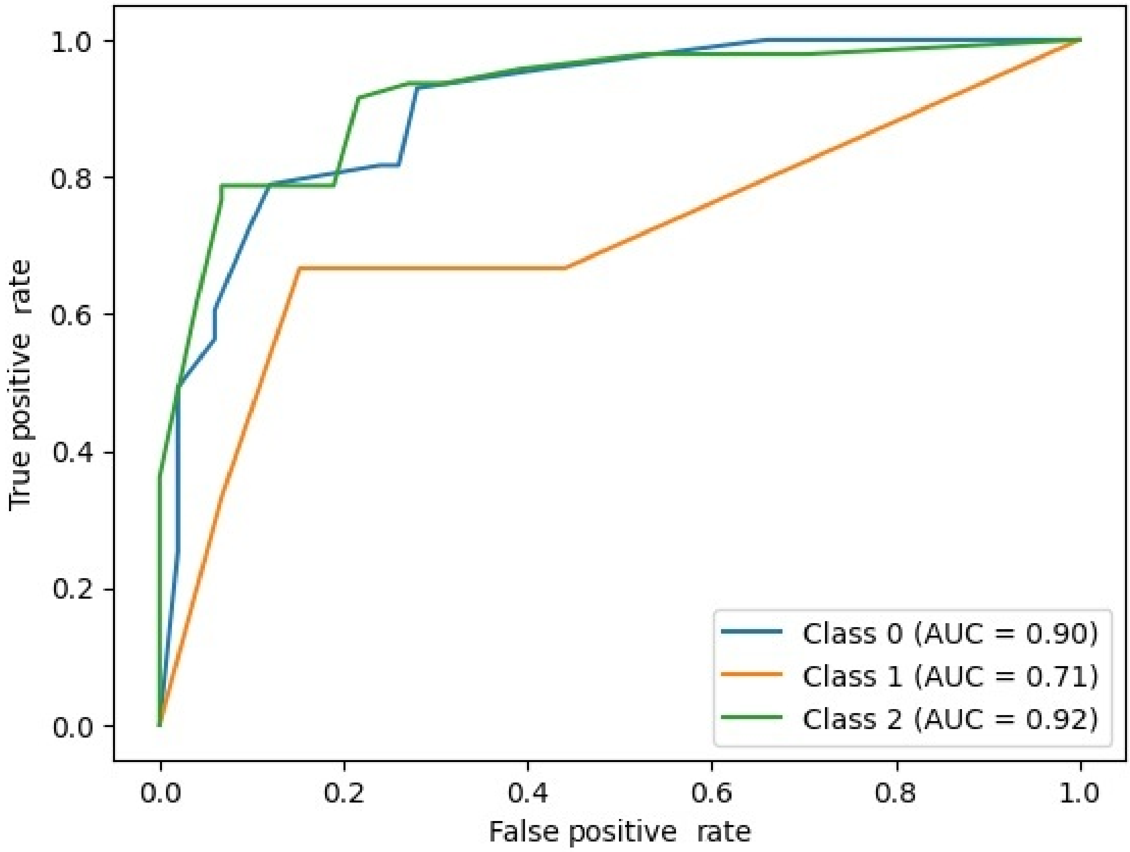

Figure 10. Receiver operating characteristic curve of the decision tree model on the test set. Abbreviation: AUC: Area under the curve

dataset size grows, requiring efficient resource management. Furthermore, while metaheuristic methods effectively explore large search spaces, there remains a trade-off between exploration and exploitation that can influence convergence speed. Future research should explore adaptive metaheuristic techniques that dynamically adjust search strategies to improve efficiency. Despite these advantages, challenges remain in terms of computational cost and convergence speed, particularly for large-scale datasets. Future research could address these limitations by exploring adaptive metaheuristic techniques that dynamically adjust search strategies to balance exploration and exploitation. Additionally, extending this approach to deep learning architectures could further enhance model performance, particularly in complex tasks such as image recognition and natural language processing. Incorporating real-time optimization techniques would also enable models to dynamically adapt to evolving data streams, thereby enhancing their robustness in real-world applications. Overall, this research provides a strong foundation for future studies on hybrid optimization techniques, highlighting their potential to revolutionize parameters tuning in ML and drive innovation across multiple disciplines.

8. Conclusion

In conclusion, the research successfully demonstrates the performance of hybrid models combining ML and metaheuristic optimization for parameter selection. The integration of metaheuristic techniques such as PSO, ABC, and GSA enhances the efficiency and accuracy of ML models by optimizing hyperparameters in a structured and automated manner. The results confirm that this approach outperforms traditional grid and random search methods, reducing computational time and improving predictive accuracy. These findings offer practical applications in various domains that require high-accuracy predictive modeling, including healthcare, finance, and engineering. In healthcare, optimized models can enhance early disease detection and personalized treatment recommendations. In finance, metaheuristic-based models improve risk assessment and market forecasting. Similarly, in engineering, these methods contribute to process optimization and failure prediction, leading to increased system reliability and efficiency. By addressing challenges inherent in high-dimensional and noisy datasets, this hybrid approach not only improves predictive accuracy but also reduces computational overhead. Furthermore, the study explores the clinical utility of the proposed models in detecting and managing stroke risks, offering practical solutions for early diagnosis and targeted intervention. Through this work, we demonstrate the transformative potential of combining metaheuristic optimization with ML in real-world healthcare applications, paving the way for more reliable, data-driven decision-making in medical practice. Using the optimized parameters obtained from the metaheuristic algorithms, the predictive accuracy of the new models improved, thereby supporting clinicians in detecting ischemic stroke. This approach reduced the time required to evaluate patients' symptoms during annual healthcare examinations.

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Conflict of interest

The authors confirm no conflicts of interest.

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Ethics approval and consent to participate

The study was conducted in compliance with institutional ethics and data protection standards, with approval (or waiver) obtained from the relevant review board. All records were fully de-identified prior to analysis, ensuring that no personally identifiable information was retained. The real dataset cannot be publicly shared due to confidentiality agreements; however, synthetic examples are available upon reasonable request for reproducibility purposes. The dataset was approved under number 200/QĐ-PKĐK on July 23, 2025, by the Ethics Committee in Biomedical Research, Pham Ngoc Thach University of Medicine.

Consent for publication

Not applicable.

Availability of data

Not applicable.

AI tools statement

All authors confirm that no AI tools were used in the preparation of this manuscript.

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