

Metaheuristic feature optimization using GA, PSO, and HHO for AWWs data classification

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ABSTRACT

Annual Wellness Visits (AWVs) generate large volumes of clinical and laboratory data that can support predictive healthcare analytics. However, the high-dimensional nature of healthcare datasets often introduces redundant and irrelevant variables, which may negatively affect model performance and computational efficiency. This study proposes a hybrid framework that integrates metaheuristic feature selection techniques with machine learning and deep learning models to improve predictive analysis using AWWs data. Three optimization algorithms, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Harris Hawks Optimization (HHO), were employed to identify informative feature subsets from a dataset containing 2,518 patient records and 53 clinical attributes. The selected features were subsequently used to train several machine learning classifiers and deep learning architectures, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) models. Experimental results demonstrate that metaheuristic optimization effectively reduces dataset dimensionality while maintaining strong predictive performance. The feature selection process successfully identified compact subsets of clinically relevant variables, leading to improved model efficiency and reduced computational complexity. Comparative analyses indicate that optimized feature subsets improve classification performance across multiple learning algorithms, while deep learning models exhibit high training capability on the AWWs dataset. The findings highlight the importance of combining feature selection with advanced predictive models to improve healthcare data analysis and support data-driven clinical decision-making. The proposed structure provides an effective approach for handling high-dimensional healthcare datasets and offers a foundation for the development of intelligent clinical decision-support systems. Future work will focus on validating the structure using larger multi-center datasets and incorporating explainable artificial intelligence techniques to improve model interpretability and clinical applicability.



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1. Introduction

Metaheuristic algorithms are often used to maximize the accuracy of feature selections. They have been developed and improved to handle complex optimization issues in a variety of domains. As demonstrated by structural engineering applications that comply with the American Institute of Steel Institution's Allowable Stress Design Code criteria, these techniques are very helpful in meeting design restrictions, safety, and durability requirements. Biogeography-Based Optimization, Dynamic Harmony Search, Wolf Colony Algorithm, and Honey Badger Algorithm are examples of metaheuristic algorithms that have proven dependable in resolving complicated problems and guaranteeing accurate outcomes.¹ Furthermore, the interval-based method offers a robust framework for modeling uncertainty in green production systems by using stochastic representations of fault rates and demand.² Furthermore, prey-inspired algorithms such as the Grey Wolf Optimizer, Sailfish Optimizer, Harris Hawk Optimizer, Aquila Optimizer, and Bat Optimizer have proven successful in handling complex engineering and optimization tasks.³ Additionally, metaheuristics provide good substitutes for traditional chemical engineering optimization techniques, such as integrating Model Predictive Control with Ant Colony Optimization, GA, and Simulated Annealing.⁴ In order to efficiently address large-scale optimization issues, novel algorithms such as the Artificial Protozoa Optimizer and Arctic Puffin Optimizer mimic natural behaviors.⁵ Metaheuristic approaches like the Artificial Immune System and GA perform better than conventional algorithms in transportation and vehicle routing, especially in situations involving cargo consolidation.⁶

An annual wellness visit, also known as an annual physical exam, is a routine check-up with a doctor to assess overall health and identify any potential problems. Prompt intervention and early disease identification are made possible by this proactive and preventative approach to health preservation. The Access Gap, a novel approach to evaluating health care access disparities, is defined as the gap between available financial resources and the out-of-pocket cost of accessing quality medical care.⁷ Non-patient-related factors are increasingly acknowledged to play a role in the use of coercive measures in mental health care, which is a significant indicator of the quality of care being offered. The purpose of the study is to investigate the opinions of mental health care providers who have direct experience

with coercion on the contextual elements that affect their use in Portuguese mental health care.⁸ Issues of justice and equity are prevalent. Many healthcare organizations reaffirmed their commitments to health equity following the events of 2020, probably because it was the right thing to do rather than because they were compelled to.⁹ The paper presents data on the distribution of hemophilia medication trials worldwide and poses queries on the ethics, opportunities, challenges, and generalizability of trials for a rare bleeding disorder.¹⁰ The goal is to evaluate the impact of digital interventions on occupational health care and the body of available evidence.¹¹

In order to improve patient-centered care, surveys measuring patients' experiences with healthcare are frequently used in general medicine. However, the patient's experience receiving oral health care is not always captured by such questionnaires. There is an urgent need to quantify patient experience in the oral health care environment because the experience is a crucial aspect of oral health care.¹² Critical care societies propose that family members be included in patient care in the intensive care unit. Nevertheless, no validated instruments currently exist to gauge family involvement in the intensive care unit.¹³ According to estimates of substantial health-related suffering, palliative care is desperately needed, especially in low- and middle-income nations.¹⁴ At the regional health care network level, this study aimed to develop a strategy to prevent the spread of multi-drug-resistant *Enterobacteriaceae*.¹⁵ Young persons who have received care, including those who are neurodivergent, have worse mental health outcomes than their peers who have not. Developing more effective and supportive services requires a thorough understanding of this population's mental health, including how it evolves over time.¹⁶ The use of coercive measures, especially mechanical and pharmacological restraints, in mental health services and disability care settings is examined in this article from a bioethical standpoint, with an emphasis on the effects these practices have on the human rights of people with mental disorders.¹⁷

The purpose of this study is to assess how well routinely gathered electronic health record data can identify clinical work that is more likely to experience burnout and may require the most focused interventions.¹⁸ There were no significant changes in the approachability of care (i.e., having a regular source of care), despite significant advancements in measures of cost (i.e., paying medical bills), care availability, and accommodation (i.e., unmet needs).¹⁹ To eliminate tuberculosis

in the United States, it is essential to prevent the disease by diagnosing and treating latent tuberculosis infection. In safety-net primary care settings that treat individuals at risk for tuberculosis, diagnosing and treating latent tuberculosis infection may boost prevention effort and accelerate the elimination process.²⁰ Across patient diagnoses, machine learning predicts hospital patients' demand for post-acute care based on an admission mobility measure.²¹ The purpose of this study is to assess how well primary care physicians follow the recommendation to take a patient's blood pressure at the first appointment.²²

To improve the effectiveness of healthcare prediction, this study employs metaheuristic optimization algorithms to identify the most informative features from AWVs datasets. Feature selection plays a crucial role in reducing data dimensionality, eliminating redundant information, and enhancing the predictive capability of machine learning models. Three widely used optimization techniques, namely GA, PSO, and HHO, are utilized to determine optimal feature subsets from demographic, clinical, laboratory, and diagnostic examination records.^{23–26}

Recent advances in machine learning and deep learning have demonstrated remarkable performance in a variety of applications, including healthcare analytics, natural language processing, image analysis, and scientific computing.^{27–29} Motivated by these successes, this study investigates the application of deep learning architectures for the prediction of AWVs outcomes. Specifically, four convolution-based recurrent learning models are considered, including Convolution Bidirectional Long Short-Term Memory (CBSLSTM), Convolution Bidirectional Gated Recurrent Unit (CBSGRU), Convolution Bidirectional Recurrent Neural Network (CBSRNN), and a hybrid Convolution Bidirectional LSTM-GRU model (CBSLSTMGRU).³⁰

Recent advances in healthcare have highlighted the growing role of digital technologies, artificial intelligence (AI), and data-driven decision-making in improving healthcare quality, accessibility, and patient outcomes. Trust remains a critical factor in the adoption of digital healthcare solutions, influencing both healthcare professionals' and patients' willingness to engage with emerging technologies.³¹ In parallel, AI-driven personalized medicine is transforming healthcare practices and education by providing more individualized diagnostic and treatment strategies.³² Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated re-

markable effectiveness in medical image analysis, including melanoma detection and cancer diagnosis, while metaheuristic optimization techniques have been increasingly employed to improve model performance and classification accuracy.^{33,34} The effectiveness of such optimization methods has been validated across various domains, including simulation optimization, imbalanced classification problems, remote sensing object detection, and environmental prediction tasks.^{35–38}

Beyond technological advancements, healthcare systems continue to face challenges related to resource allocation, accessibility, and service quality. Studies have demonstrated significant associations between healthcare resources and population health outcomes, emphasizing the need for efficient healthcare management strategies.³⁹ Mobile healthcare services have emerged as an effective approach to reducing disparities in rural areas and improving healthcare access,⁴⁰ while investigations of post-COVID-19 healthcare utilization have revealed persistent inequities and unmet healthcare needs among vulnerable populations.⁴¹ Additional research has examined healthcare costs in emergency care settings,⁴² healthcare workforce engagement and quality improvement initiatives,⁴³ and patient satisfaction in cross-boundary healthcare services.⁴⁴ Furthermore, healthcare education and public engagement remain essential components of healthcare system development, as demonstrated by studies on healthcare conferences for students, vaccination mobilization campaigns, and healthcare professionals' experiences in elderly care services.^{45–47} Collectively, these studies indicate that integrating advanced AI techniques with effective healthcare management strategies can contribute substantially to improving healthcare quality, accessibility, and sustainability.

Recent advances in deep learning have demonstrated remarkable success across a wide range of image analysis applications. In medical imaging, Aslan and Özüpak⁴⁸ proposed a hybrid VGG19-U-Net structure for brain tumor segmentation from MRI images, achieving highly accurate delineation of tumor regions through the integration of feature extraction and semantic segmentation capabilities. Similarly, Kör and Mazman⁴⁹ developed a convolutional neural network-based approach for brain tumor detection and classification, highlighting the effectiveness of deep learning architectures in supporting automated medical diagnosis. Beyond healthcare applications, deep learning models have also shown

strong performance in agricultural and remote sensing domains. Aslan and Özupak⁵⁰ introduced a hybrid SE-ResNet50 structure for cotton leaf disease classification, demonstrating the benefits of attention mechanisms in improving classification accuracy and model interpretability. In addition, Aslan and Özupak⁵¹ applied deep learning techniques to road extraction from satellite imagery, illustrating the capability of convolutional architectures to capture complex spatial patterns in high-resolution remote sensing data. Collectively, these studies confirm the versatility and effectiveness of deep learning models in addressing challenging image segmentation, classification, and feature extraction tasks across diverse application domains.

The experimental evaluation is conducted using four AWWs datasets collected from 2022 to 2025, comprising a total of 2,518 health examination records (**Table 1**). These datasets contain diverse

health-related attributes, including physical examination measurements, imaging findings, laboratory test results, and clinical diagnoses. The selected features obtained from the metaheuristic optimization algorithms are used as inputs to the deep learning models for classification and prediction tasks. The primary objective of this research is to develop an efficient prediction framework capable of accurately identifying health conditions from routine wellness examination data. Furthermore, by determining the most influential medical indicators, the proposed framework can assist healthcare providers in prioritizing essential examinations, thereby reducing unnecessary testing, lowering healthcare costs, and improving the efficiency of annual wellness screening programs. The findings of this study contribute to the development of intelligent healthcare systems and support data-driven decision-making in preventive medicine and personalized health management.

Table 1. Representative samples extracted from the healthcare datasets (2022–2025). All data were anonymized and encoded prior to analysis to protect participant privacy and prevent the disclosure of personally identifiable information.

Year	NID	Gender	Height	Weight	BMI	Pulse	Internal Medicine	Conclusion
2022	N001	Male	170	68	23.5	72	Normal	Healthy
2022	N002	Female	158	52	20.8	76	Normal	Healthy
2022	N003	Male	172	75	25.4	80	Follow-up	Fatty liver
2022	N004	Female	160	58	22.7	70	Normal	Healthy
2022	N005	Male	168	71	25.2	78	Follow-up	Hyperlipidemia
2023	N006	Female	162	55	21.0	74	Normal	Healthy
2023	N007	Male	174	77	25.4	79	Follow-up	Hypertension
2023	N008	Female	159	50	19.8	72	Normal	Healthy
2023	N009	Male	171	80	27.4	82	Follow-up	Diabetes risk
2023	N010	Female	165	57	20.9	75	Normal	Healthy
2024	N011	Male	169	73	25.6	77	Follow-up	Hyperlipidemia
2024	N012	Female	160	53	20.7	71	Normal	Healthy
2024	N013	Male	173	76	25.4	80	Follow-up	Fatty liver
2024	N014	Female	161	54	20.8	74	Normal	Healthy
2024	N015	Male	170	82	28.4	84	Follow-up	Hypertension
2025	N016	Female	158	51	20.4	73	Normal	Healthy
2025	N017	Male	175	79	25.8	81	Follow-up	Hyperlipidemia
2025	N018	Female	163	56	21.1	72	Normal	Healthy
2025	N019	Male	172	78	26.4	83	Follow-up	Fatty liver
2025	N020	Female	160	55	21.5	75	Normal	Healthy

2. Fundamental concepts

Optimization techniques play a crucial role in identifying the most informative features and determining optimal parameter settings for machine learning models. The primary objective of optimization is to maximize predictive performance while minimizing computational complexity and

redundancy in the feature space. Metaheuristic optimization algorithms have been widely adopted because of their ability to efficiently explore large and complex search spaces without requiring gradient information. Among the most popular methods are PSO, Grey Wolf Optimization (GWO), Ant Colony Optimization (ACO), GA, Cuckoo Search Algorithm (CSA), and HHO.

In this study, three powerful metaheuristic optimization techniques, namely GA, PSO, and HHO, are employed for feature selection and performance comparison.

2.1. Genetic algorithm

GA is inspired by the principles of natural evolution, including selection, crossover, and mutation. A fitness function is used to evaluate the quality of candidate solutions:

$$F(x) = \text{Fitness of solution } x,$$

where $F(x)$ represents the fitness value associated with solution x . The objective is to maximize or minimize $F(x)$ depending on the optimization problem.

The probability of selecting a solution is determined by

$$P(x) = \frac{F(x)}{\sum_{i=1}^n F(x_i)},$$

where $P(x)$ denotes the selection probability of solution x and n is the population size.

Crossover combines two parent solutions to generate offspring solutions. Given two parent solutions x_1 and x_2 , the crossover operation can be expressed as

$$x_3, x_4 = \text{Crossover}(x_1, x_2).$$

Mutation introduces diversity into the population by randomly modifying selected genes:

$$x' = \text{Mutation}(x).$$

These evolutionary operators enable GA to balance exploration and exploitation during the search process.

2.2. Particle swarm optimization

PSO is a population-based optimization technique inspired by the collective behavior of bird flocks and fish schools. Each particle adjusts its trajectory according to both its personal best experience and the global best solution found by the swarm.

The velocity update equation is given by

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

where $v_i(t)$ denotes the velocity of particle i at iteration t , w is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers in $[0, 1]$, p_i is the personal best position, and g is the global best position.

The position of each particle is subsequently updated as

$$x_i(t+1) = x_i(t) + v_i(t+1),$$

where $x_i(t)$ represents the position of particle i at iteration t .

2.3. Harris hawks optimization

HHO is a nature-inspired metaheuristic algorithm proposed by Heidari *et al.*, which mimics the cooperative hunting strategy of Harris hawks.^{23–26} The algorithm alternates between exploration and exploitation phases depending on the escaping energy of the prey.

The prey energy is modeled as

$$E = 2E_0 \left(1 - \frac{t}{T}\right),$$

where E_0 is the initial energy randomly generated in the interval $[-1, 1]$, t denotes the current iteration, and T is the maximum number of iterations.

During the exploration phase ($|E| \geq 1$), hawks explore different regions of the search space using

$$X(t+1) = X_{rand}(t) - r_1 |X_{rand}(t) - 2r_2 X(t)|,$$

where X_{rand} denotes a randomly selected hawk and $r_1, r_2 \in [0, 1]$ are random coefficients.

When $|E| < 1$, the algorithm enters the exploitation phase, where hawks perform soft or hard besiege strategies around the prey. A commonly used position update rule is

$$X(t+1) = X_{prey}(t) - E |JX_{prey}(t) - X(t)|,$$

where X_{prey} denotes the best solution found so far and

$$J = 2(1 - r_3)$$

represents the jump strength of the prey with $r_3 \in [0, 1]$.

The adaptive transition between exploration and exploitation enables HHO to effectively avoid local optima and achieve competitive performance in feature selection and optimization problems.

2.4. Convolution bidirectional learners

Convolution bidirectional learners (CBLs), consisting of convolution layers, bidirectional repeaters, and learners such as LSTM, GRU, and RNN, are utilized. The integration of these models results in innovative architectures such as the simple bidirectional recurrent neural network (CBSRNN), the convolution bidirectional gated recurrent unit (CBGRU), the convolution bidirectional long short-term memory (CBLSTM), and mixed variants combining these structures.²⁷ In particular, CBLs are effective for predicting student feedback on library service quality in natural language processing tasks with labeled data.^{29,30}

The CBL structures of CBRNNLSTM and CBRNNGRU are displayed in **Figures 1** and **2**. The inputs are concatenated to produce control-directed data based on the robust convolution layer before being passed to the subsequent layers. Using a bidirectional layer, the minibatch

is routinely trained to focus on prediction. The purpose of this layer is to use structured data to connect to the output layers.

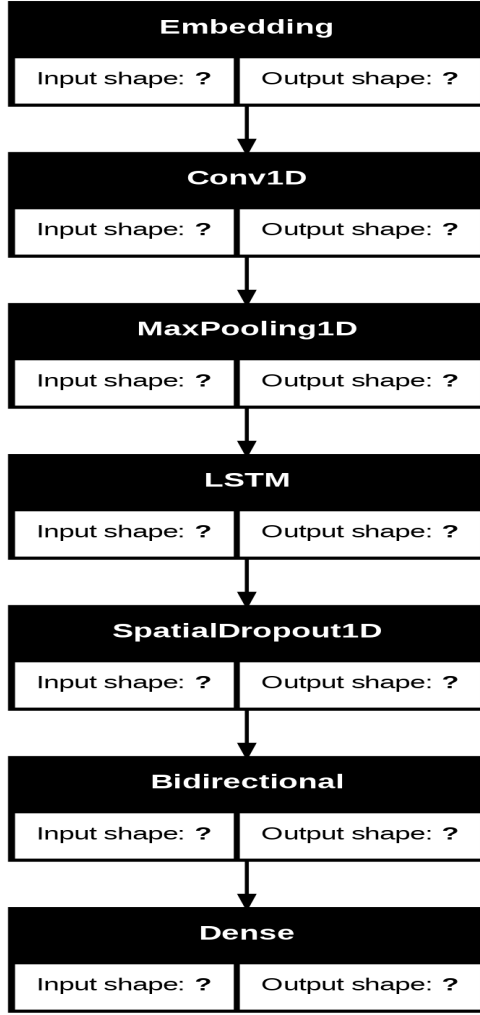


Figure 1. CBRNNLSTM model

3. Data collection and methodology

3.1. Data collection

The experimental study was conducted using four AWWs datasets collected from 2022 to 2025. These datasets comprise a total of 2,518 health examination records obtained from periodic medical check-ups. Each dataset contains a diverse set of demographic information, physical examination results, laboratory measurements, imaging findings, and clinical diagnostic outcomes. The collected attributes include anthropometric measurements (e.g., height, weight, and body mass index), vital signs (e.g., blood pressure and pulse rate), clinical examinations (e.g., internal medicine, surgery, ophthalmology, otorhinolaryngology, and gynecology), imaging assessments (e.g., chest X-ray, electrocardiography, abdominal

ultrasound, thyroid ultrasound, and echocardiography), as well as biochemical and hematological indicators such as glucose, creatinine, AST, ALT, cholesterol, triglycerides, HBsAg, HCT, and MCHC.

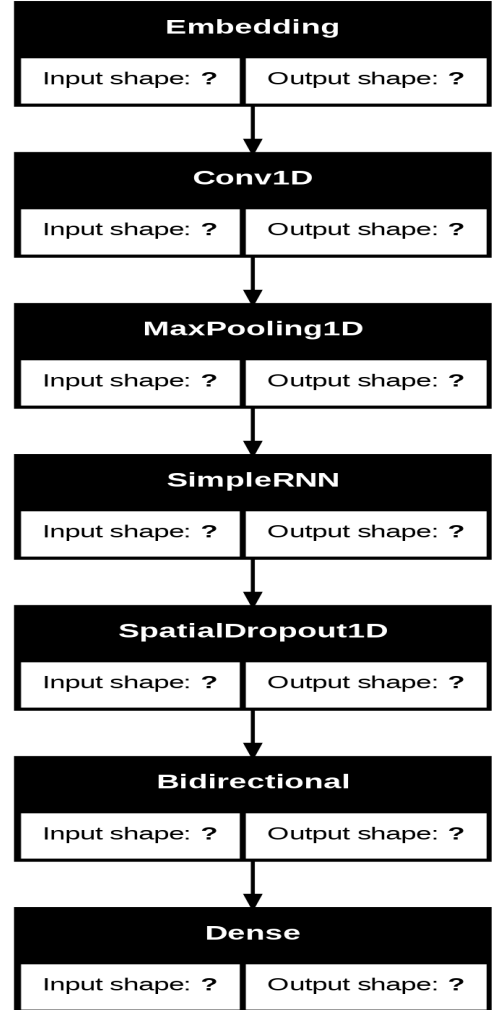


Figure 2. CBRNNGRU model

After data preprocessing and cleaning, the datasets contained between 11 and 53 available features depending on the year. Missing values, duplicated records, and irrelevant attributes were removed before the feature selection process. The resulting datasets were subsequently used to evaluate the effectiveness of the proposed feature selection and classification framework.

3.2. Dataset description

The target variable represents the overall health assessment outcome assigned by medical professionals during the AWWs process. Based on comprehensive clinical evaluation, each participant was categorized into one of three classes: positive, neutral, or negative. The positive class corresponds to individuals with clinically normal

conditions and no significant abnormalities detected during examination. The neutral class includes individuals presenting mild abnormalities or health conditions requiring periodic monitoring but not immediate medical intervention. The negative class represents individuals with clinically significant abnormalities that warrant further diagnostic investigation, specialist consultation, or medical treatment. These class labels were determined through an integrated assessment of laboratory test results, electrocardiogram (ECG) findings, physical examination outcomes, diagnostic imaging results, and physician evaluations, thereby reflecting the overall health status of each participant. The complete dataset used in this study consists of 2,518 AWVs records collected between 2022 and 2025. In addition, the representative patient records presented in **Table 1** are anonymized examples intended solely to illustrate the structure and characteristics of the collected data. These records were utilized throughout the entire experimental workflow, including feature selection, model training, validation, and performance evaluation. For descriptive purposes, **Table 2** provides clinical descriptions of the variables included in the dataset together with their medical significance. The annual sample distributions are summarized in **Table 3**, comprising 603 records from 2022, 688 records from 2023, 624 records from 2024, and 603 records from 2025. **Table 4** provides the intersection of the attributes. These examples should not be interpreted as representing the complete dataset used

in the experiments. To further assess the practical applicability of the proposed models, an independent test subset containing 151 instances was employed for comparison with direct physician evaluations. This test subset was derived from the overall dataset and reserved exclusively for final performance assessment. Consequently, the 151 instances reported in the evaluation set and separate from the complete dataset of 2,518 records used for model development and optimization.

3.3. Model construction

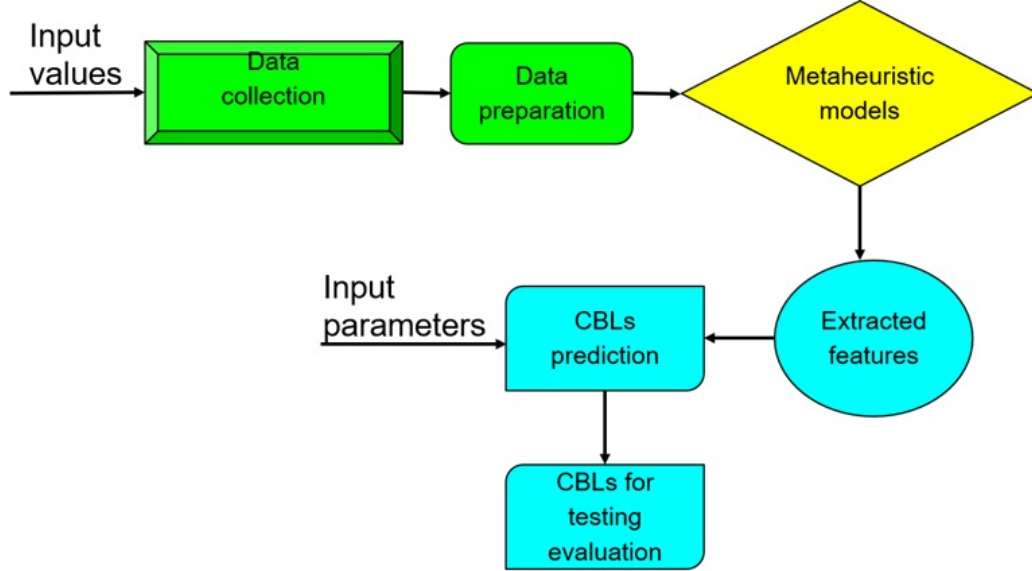
The overall methodology of the proposed framework consists of five major stages: data preprocessing, feature selection, feature optimization, classification, and performance evaluation, as illustrated in **Figure 3**. Initially, the raw AWVs datasets undergo preprocessing in which missing values are handled, categorical variables are encoded, numerical features are normalized, and inconsistent records are removed. This step ensures data quality and improves the reliability of subsequent analyses. Following preprocessing, meta-heuristic optimization algorithms are employed to identify the most informative subset of features. In this study, three optimization methods, namely GA, PSO, and HHO, are investigated and compared. These algorithms search the feature space to maximize classification performance while minimizing the number of selected attributes. By eliminating redundant and irrelevant features, the optimization process reduces computational complexity and improves model interpretability.

Table 2. Clinical description of the variables included in the AWVs dataset

Feature	Description	Clinical significance
Age	Participant age (years)	Important demographic risk factor associated with chronic diseases.
Gender	Biological sex of participant	Influences disease prevalence and physiological characteristics.
BMI	Body Mass Index (kg/m ²)	Indicator of obesity and metabolic health.
HGB	Hemoglobin concentration	Reflects oxygen-carrying capacity and anemia status.
MCV	Mean Corpuscular Volume	Assesses red blood cell size and hematological disorders.
PCT	Plateletcrit	Indicator of platelet volume and thrombosis-related conditions.
MONO1	Monocyte count	Associated with immune response and inflammatory processes.
ECG	Electrocardiogram assessment result	Evaluates cardiac electrical activity and cardiovascular abnormalities.
NoiKhoa	Internal medicine examination outcome	Comprehensive physician assessment of overall health status.

Table 3. Summary of HHO feature selection results from 2022–2025

Year	Samples	Initial features	Selected features	Accuracy (%)
2022	603	30	16	43.18
2023	688	11	10	57.89
2024	624	35	14	97.50
2025	603	53	12	94.21

**Figure 3.** Constructing steps for optimal and CBLs prediction**Table 4.** Frequently selected features across multiple years

Feature	Years appearing
Chest X-ray	2022, 2023, 2025
ECG	2022, 2023, 2025
Creatinine	2022, 2024, 2025
Gynecological Examination	2022, 2024, 2025
HBsAg	2024, 2025
AST	2022, 2024
Triglycerides	2022, 2024
Weight/BMI	2022, 2023, 2025

The selected feature subsets are then used as inputs to the classification model. The learning framework is trained using the optimized feature sets to capture relationships among demographic, clinical, laboratory, and diagnostic variables. The dataset is divided into training and testing subsets to ensure an unbiased evaluation of predictive performance. In the evaluation stage, model performance is assessed using several quantitative metrics, including Accuracy, Precision, Recall, F1-score, Loss, and Validation Loss. These metrics provide a comprehensive assessment of classification capability and generalization performance. Finally, the obtained results are analyzed to determine the effectiveness of each feature selection

strategy. The iterative optimization process enables continuous refinement of the selected feature subsets, ultimately improving prediction accuracy while reducing data dimensionality. The combination of metaheuristic feature selection and machine learning classification provides an efficient framework for healthcare prediction using AWVs data.

3.4. Metaheuristic algorithm configuration

To ensure a fair comparison among the feature optimization methods, the parameter settings of GA, PSO, and HHO were fixed throughout all experiments. The population size and maximum number of iterations were kept identical across algorithms, while algorithm-specific parameters followed commonly used values reported in the literature. These settings were selected to balance optimization performance and computational cost while maintaining consistency across all feature selection experiments.

3.5. Fitness function

In the feature selection stage, each candidate solution is represented as a binary vector, where a value of 1 indicates that the corresponding feature is selected and 0 indicates that it is excluded. The

quality of each candidate subset is evaluated using a fitness function based on classification performance. For each candidate solution, the selected features are used to train the classifier, and the resulting accuracy is returned as the fitness score. GA, PSO, and HHO iteratively update their populations based on these fitness values until the maximum number of iterations is reached or convergence is achieved.

Let S denote the selected feature subset and $Acc(S)$ denote the classification accuracy obtained using the corresponding classifier. The fitness function takes into account both classification performance and subset compactness:

$$Fitness(S) = \alpha, Acc(S) + (1 - \alpha) \left(1 - \frac{|S|}{N} \right),$$

where $Acc(S)$ denotes the classification accuracy obtained using the selected feature subset S , $|S|$ is the number of selected features, N is the total number of available features, and $(\alpha \in [0, 1])$ controls the trade-off between predictive performance and dimensionality reduction.

3.6. Evaluation models

The CBSLSTM, CBSGRU, CBSRNN, and CBSLSTMGRU models employed in this study were adopted from our previously published work, where their architectures, hyperparameter configurations, training procedures, and comparative evaluations were described in detail. These models were selected because they consistently achieved superior predictive performance in AWWs data analysis compared to several traditional machine learning and deep learning baselines. Since the primary focus of the present study is on feature optimization rather than on neural architecture development, only a brief summary of the model structures is provided here, while complete implementation details can be found in the cited reference.

4. Experimental results

This section presents the experimental setup, feature selection outcomes, classification performance, and comparative analysis of the proposed framework. The results are summarized using tables and figures to demonstrate the effectiveness of the metaheuristic optimization algorithms and deep learning models. Since the experimental settings, optimization parameters, and implementation details have already been thoroughly reported in our previous works,^{1,30} we do not reproduce them in this paper. Interested readers may refer to these references for a complete description of the experimental configuration.

4.1. Model development

The experiments were conducted using four AWWs datasets collected between 2022 and 2025, containing a total of 2,518 health examination records. The datasets include demographic information, physical examination measurements, laboratory findings, imaging assessments, and clinical diagnostic indicators. Prior to model construction, data preprocessing procedures including missing-value handling, normalization, categorical encoding, and feature standardization were applied to ensure data consistency and quality.

To identify the most informative attributes, three metaheuristic optimization algorithms were employed: GA, PSO, and HHO. Each algorithm searches the feature space iteratively to maximize classification performance while minimizing the number of selected features. The optimization process evaluates candidate feature subsets through a fitness function based on prediction accuracy, allowing the algorithms to balance exploration and exploitation during the search process.

For PSO, candidate solutions are represented as particles moving within the search space. Their positions are updated according to individual and global best solutions, providing efficient convergence toward optimal feature subsets. Similarly, GA evolves populations of candidate solutions through selection, crossover, and mutation operations. HHO mimics the cooperative hunting behavior of Harris hawks, dynamically alternating between exploration and exploitation phases according to the prey's escaping energy. This adaptive mechanism enables HHO to avoid local optima and improve feature selection quality.

The selected feature subsets obtained from each optimization algorithm were subsequently used as inputs to the deep learning prediction models. Four convolution-based bidirectional learning architectures were investigated, namely Convolution Bidirectional Long Short-Term Memory (CBSLSTM), Convolution Bidirectional Gated Recurrent Unit (CBSGRU), Convolution Bidirectional Recurrent Neural Network (CBSRNN), and the hybrid Convolution Bidirectional LSTM-GRU (CBSLSTMGRU). These models were designed to capture complex nonlinear relationships among clinical, laboratory, and diagnostic variables extracted from the AWWs datasets.

The datasets were divided into training and testing subsets using a stratified sampling strategy to preserve class distributions. During training, model parameters were optimized through back-propagation, while validation data were used to

monitor convergence and prevent overfitting. The predictive performance of each model was evaluated using Accuracy, Precision, Recall, F1-score, Loss, and Validation Loss metrics.

Figures 4–7 illustrate the convergence behavior of the feature selection algorithms and the evolution of fitness values throughout the optimization process. The selected feature subsets for each dataset year are summarized in **Table 5**. Furthermore, **Figures 8–11** present the learning curves and prediction performance of the CBSLSTM, CBSGRU, CBSRNN, and CBSLSTMGRU models, respectively (**Table 6**). One possible explanation for the lower accuracy observed in the 2022 and 2023 datasets is that fewer informative features were selected, which may have limited the discriminative capability of the resulting models. Conversely, the larger feature sets available in the 2024 and 2025 datasets likely provided more informative patterns, leading to improved optimization and higher classification accuracies.

The experimental results demonstrate that metaheuristic feature selection substantially reduces the dimensionality of the datasets while maintaining or improving predictive performance. Among the investigated optimization techniques, HHO consistently achieved highly competitive feature subsets with fewer selected attributes. The optimized feature sets enabled the deep learning models to achieve high classification accuracy, indicating the effectiveness of combining metaheuristic optimization with convolution-based bidirectional learning architectures for healthcare prediction tasks. The overall findings confirm

that the proposed framework can effectively identify critical medical indicators, reduce redundant examinations, and improve prediction accuracy for AWWs outcomes. These results provide valuable support for intelligent healthcare systems and data-driven clinical decision-making.

4.2. Analysis of selected features from 2022–2025

Table 3 summarizes the datasets, selected features, and classification performance obtained using the HHO feature selection algorithm from 2022 to 2025. The results indicate that HHO effectively reduced the dimensionality of the healthcare datasets while maintaining high predictive performance. The highest accuracy was achieved in 2024 (97.50%), followed by 2025 (94.21%).

4.2.1. Selected features by year

The selected healthcare features varied across the datasets collected from 2022 to 2025, reflecting differences in medical priorities, patient conditions, and optimization outcomes over time. In 2022, the selected features mainly focused on metabolic indicators, imaging diagnostics, and biochemical examinations. These included BMI, systolic and diastolic blood pressure, surgical examination, gynecological examination, eye examination, abdominal ultrasound, echocardiography, breast ultrasound, ECG, chest X-ray, AST, ALT, creatinine, cholesterol, and triglycerides. The results indicate that cardiovascular, liver, and metabolic screening indicators played an important role in the early-stage healthcare assessment.

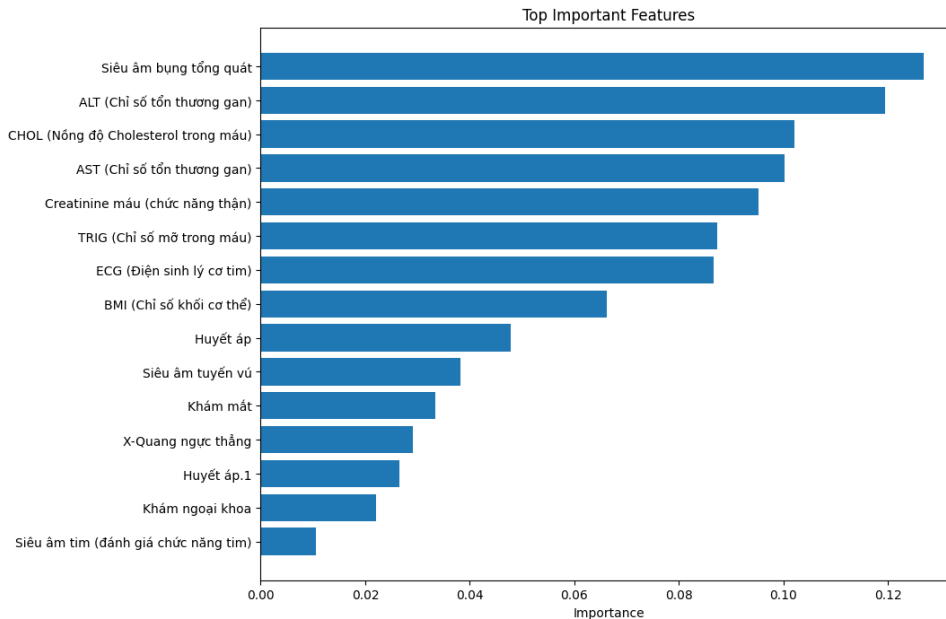


Figure 4. Feature importance and selected attributes obtained from the 2022 AWWs dataset using HHO

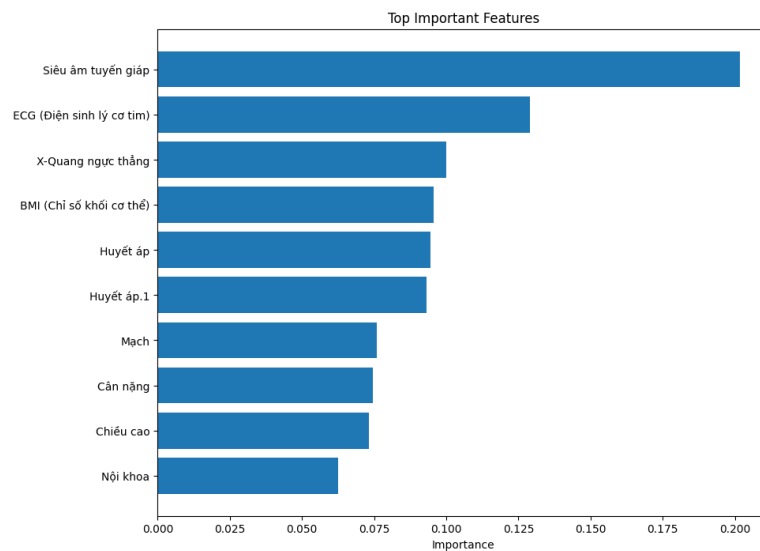


Figure 5. Feature importance and selected attributes obtained from the 2023 AWWs dataset using Harris Hawks Optimization (HHO)

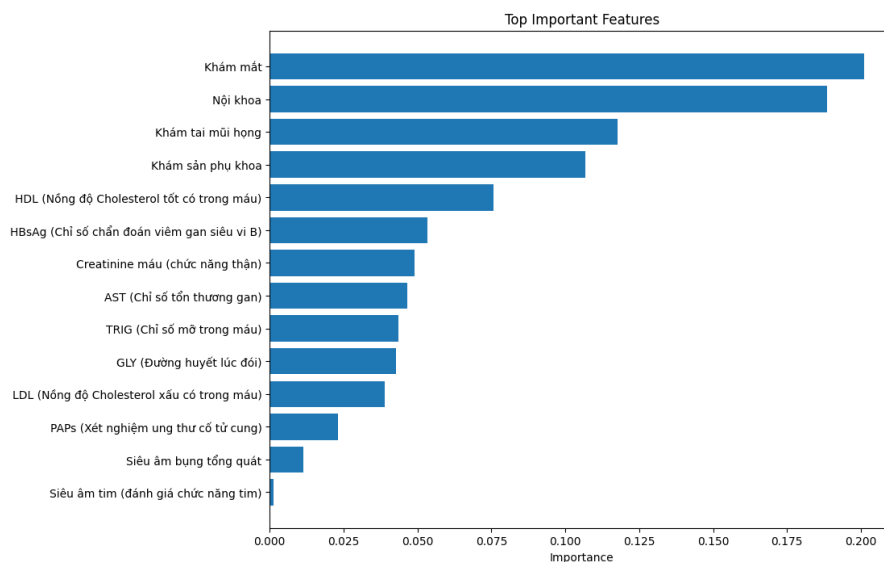


Figure 6. Feature importance and selected attributes obtained from the 2024 AWWs dataset using HHO

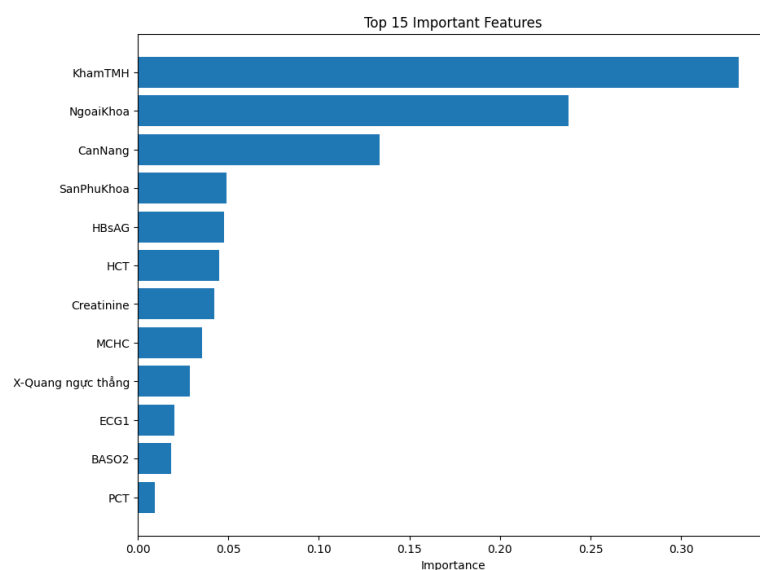


Figure 7. Feature importance and selected attributes obtained from the 2025 AWWs dataset using HHO

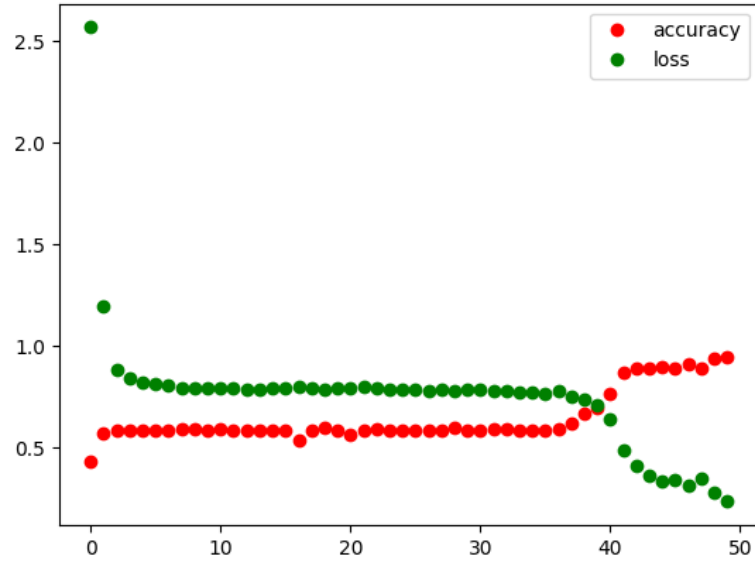


Figure 8. CBRNNLSTM prediction

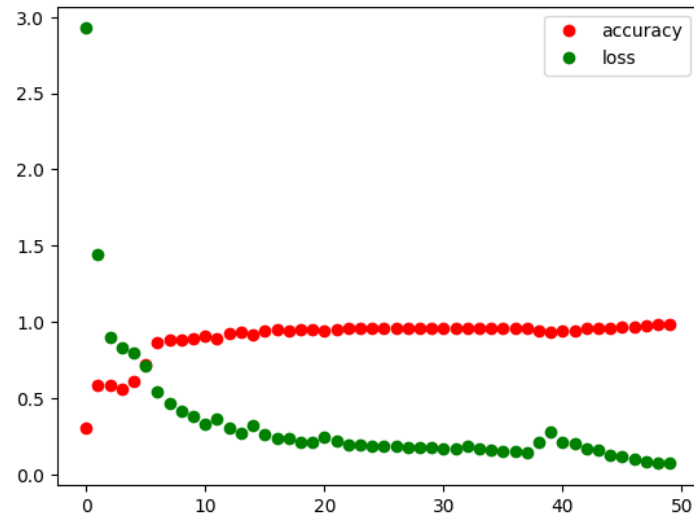


Figure 9. CBRNNGRU prediction

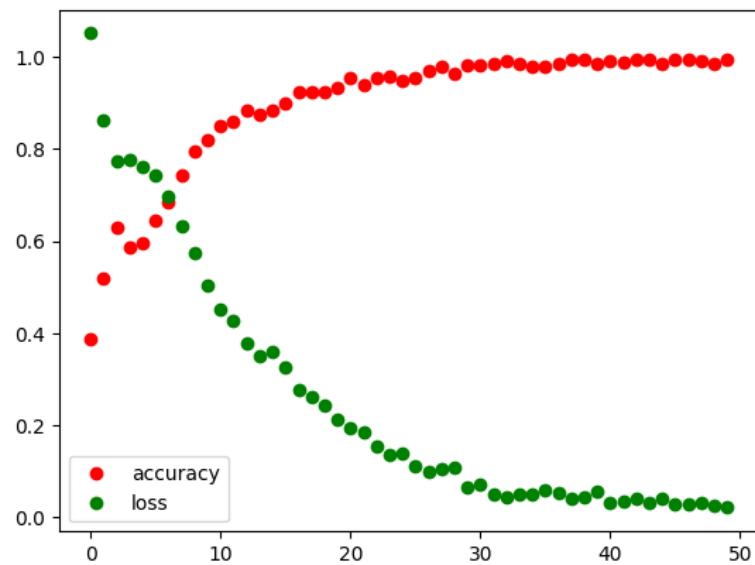


Figure 10. CBRNN prediction

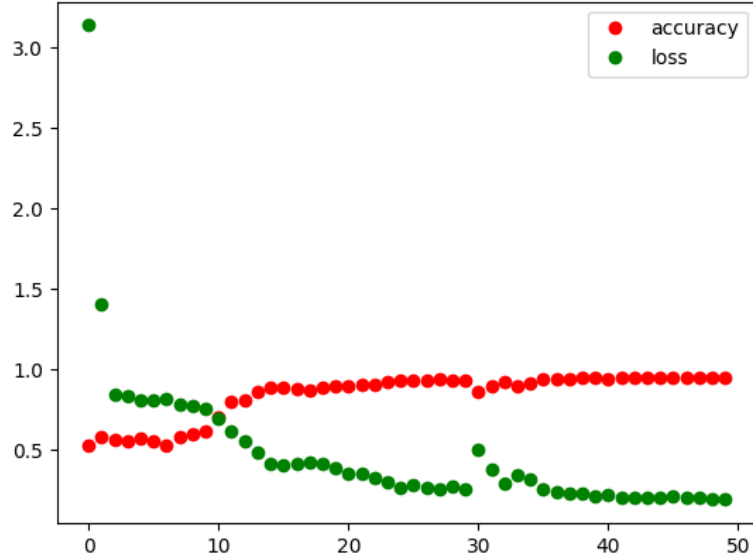


Figure 11. CBRNNGRU prediction

Table 5. Summary of feature selection performance obtained using HHO on AWVs datasets

Metric	HHO			
	G1 (2022)	G2 (2023)	G3 (2024)	G4 (2025)
Selected Features	16	10	14	12
Accuracy	0.4318	0.5789	0.9750	0.9421
Fitness Value	0.5281	0.4386	0.419	0.519

Table 6. CBLs prediction for new selection features. The features are selected from G1 in Table 1

Learners	Accuracy	Loss	Val-accuracy	Val-loss
CBSLSTM	0.9456	0.2172	0.8013	0.6020
CBSLSTMGRU	0.9494	0.2241	0.7682	0.9019
CBSGRU	0.9799	0.0852	0.7152	0.1110
CBSRNN	0.9987	0.0176	0.8013	1.1361

In 2023, the selected features shifted toward fundamental physiological measurements and internal clinical evaluations. The optimized subset consisted of height, weight, BMI, pulse rate, systolic and diastolic blood pressure, internal medicine examination, thyroid ultrasound, ECG, and chest X-ray. Compared with 2022, the selected attributes emphasized general physical condition and cardiovascular monitoring while reducing the number of biochemical laboratory indicators.

For the 2024 dataset, the selected features highlighted a combination of clinical examinations, imaging techniques, and biochemical laboratory tests. The optimized attributes included internal medicine examination, gynecological examination,

on, eye examination, ENT examination, PAP smear, abdominal ultrasound, echocardiography, fasting glucose, AST, creatinine, triglycerides, LDL, HDL, and HBsAg. These findings suggest that preventive screening for chronic diseases, liver conditions, and women's health became increasingly significant in the healthcare evaluation process.

In 2025, the selected features were further refined into a more compact subset emphasizing diagnostic imaging, infection-related indicators, and hematological measurements. The selected attributes included chest X-ray, ECG, weight, surgical examination, gynecological examination, ENT examination, creatinine, HBsAg, hematocrit (HCT), procalcitonin (PCT), MCHC, and

BASO2. This optimized feature subset demonstrates the importance of combining imaging-based diagnosis with blood-related biomarkers to support efficient and cost-effective annual wellness screening.

4.2.2. Common features across years

Table 4 presents the most frequently selected features. Based on the frequency of occurrence, the most stable and informative features include *Chest X-ray*, *ECG*, *Creatinine*, *Gynecological Examination*, *HBsAg*, *AST*, and *Triglycerides*. These features consistently appeared across multiple years and are therefore considered core predictors for AWVs classification.

4.2.3. Core feature set

The following feature subset can be regarded as the core feature set for the unified healthcare prediction model:

$$F_{\text{core}} = \{\text{Chest X-ray, ECG, Creatinine, Gynecological Examination, HBsAg, AST, Triglycerides, Weight, BMI, Blood Pressure, Eye Examination, Abdominal Ultrasound}\}.$$

4.3. AWVs datasets and overall results

To evaluate the effectiveness of the proposed HHO-based feature selection framework, four AWVs datasets collected between 2022 and 2025 were analyzed. The combined dataset consists of 2,518 health examination records and includes demographic information, clinical examination outcomes, imaging findings, laboratory measurements, and clinical diagnoses obtained during routine wellness assessments. The annual datasets contain 603, 688, 624, and 603 records for 2022, 2023, 2024, and 2025, respectively, reflecting variability in participant enrollment and data collection practices across years. Following data cleaning and preprocessing, including the removal of incomplete and duplicated records, the number of available features varied from 11 to 53 depending on the year. These differences arose from changes in examination protocols, laboratory tests, and clinical assessment variables recorded during different annual wellness screening programs. Despite the heterogeneous nature of the datasets, all records were processed using a consistent experimental workflow for feature selection, model training, validation, and performance evaluation. Although GA, PSO, and HHO were all implemented during the experimental phase, the comp-

arative results showed that HHO consistently achieved superior classification accuracy and selected more informative feature subsets. Therefore, for clarity and to avoid redundancy, only the detailed feature selection results obtained by HHO are presented and discussed in this study.

For each annual dataset, HHO was employed to identify the most informative subset of features before classification. The experimental results demonstrate that the proposed strategy effectively reduced the dimensionality of the datasets while preserving or improving predictive performance. Specifically, HHO selected 16, 10, 14, and 12 features for the 2022, 2023, 2024, and 2025 datasets, respectively. The corresponding classification accuracies were 43.18%, 57.89%, 97.50%, and 94.21%. An analysis of the selected features across all years reveals several consistently important medical indicators. Features such as chest X-ray findings, electrocardiogram (ECG) results, creatinine levels, gynecological examinations, HBsAg status, triglyceride measurements, and liver function markers were repeatedly selected among the optimal feature subsets. These variables represent key physiological, biochemical, and diagnostic indicators that are significant for predicting health outcomes in annual wellness examinations. Overall, the results indicate that HHO is capable of identifying compact and informative feature subsets from heterogeneous healthcare datasets. The substantial reduction in feature dimensionality, combined with high predictive accuracy in the larger and more representative datasets of 2024 and 2025, confirms the suitability of the proposed framework for supporting data-driven decision-making in AWVs analysis and healthcare prediction systems.

4.4. Performance evaluation metrics

This subsection presents the evaluation metrics used to assess the effectiveness of the proposed feature selection and prediction framework. The selected feature subsets obtained from the metaheuristic optimization algorithms, namely GA, PSO, and HHO, are summarized in **Table 5**. These optimized feature subsets were subsequently used as inputs to the deep learning models for AWVs prediction.

To evaluate the classification performance of the proposed framework, several standard metrics were employed, including Accuracy, Precision, Recall, and F1-score. Among these metrics, Accuracy was used as the primary metric for overall prediction performance and is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN},$$

where TP , TN , FP , and FN denote the numbers of true positives, true negatives, false positives, and false negatives, respectively.

To monitor the training process of the deep learning models, the categorical cross-entropy loss function was employed during training. The loss function is defined as

$$L(\theta) = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C y_{ic} \log(\hat{y}_{ic}),$$

where N represents the number of training samples, C denotes the number of classes, y_{ic} is the

actual class label, and $\hat{y}_{ic}$ is the predicted probability of sample i belonging to class c .

The predictive performance of the proposed deep learning architectures, including CBSLSTM, CBSGRU, CBSRNN, and CBSLSTMGRU, is illustrated in **Figures 8–11**. The corresponding quantitative results obtained from the AWWs datasets are summarized in **Tables 3** and **4**. These results provide a comprehensive comparison of the effectiveness of the optimized feature subsets and the investigated deep learning models in healthcare prediction tasks. **Table 7** compares the CBLs predictions with physician evaluations on the test set.

Table 7. CBLs prediction for new test dataset compared to Doctor’s evaluation. Professional Doctors in the hospital are invited to assess directly on the sample test including 151 instances

Learners	CBSLSTM	CBSLSTMGRU	CBSGRU	CBSRNN	Doctor’s evaluation
Positive	88	91	95	92	90
Negative	35	31	30	33	30
Neutral	28	29	26	26	31

4.5. Implications for heterogeneous healthcare data analytics

Beyond improving classification performance, the proposed feature optimization framework provides important insights into learning from heterogeneous healthcare data. The datasets contain between 11 and 53 attributes depending on the collection year spanning multiple modalities, including demographic characteristics, physiological measurements, hematological indicators, ECG findings, and internal medicine assessments. These modalities exhibit distinct statistical properties, scales, and distributions, making effective feature integration a challenging task in healthcare analytics.

Interestingly, the HHO-based feature optimization process selected only 10-16 features originating from different clinical modalities, namely ECG, Internal Medicine assessment, HGB, MCV, PCT, and MONO1. This observation suggests that the selected subset captures complementary and synergistic information distributed across heterogeneous data sources. Rather than relying on a single modality, the optimized feature set appears to preserve the most informative cross-modal relationships relevant to AWWs classification.

The ability to identify a compact cross-modality representation opens up several promising research directions. Future studies may investigate multimodal fusion strategies, such as cross-attention mechanisms, tensor fusion networks, and transformer-based multimodal architectures, to explicitly model interactions among the selected clinical variables. Such approaches could potentially uncover higher-order dependencies between physiological, laboratory, and clinical examination data, thereby further improving predictive performance and clinical decision support.

Moreover, the compact feature representation may facilitate graph-based healthcare analytics. Inspired by recent graph learning approaches in healthcare, patient similarity networks can be built using the selected optimized features, where each patient is represented as a node and edges encode feature-based similarity relationships. Graph Neural Networks (GNNs) can then propagate information across the patient graph to identify latent population structures and support risk stratification. Following the concept of machine learning-improved graph analytics proposed by Hang *et al.*, a patient-specific risk index could be derived by integrating local neighborhood characteristics, graph centrality measures, and model-predicted probabilities. Such a risk index may provide clinicians

with a quantitative measure of patient vulnerability while incorporating both individual clinical attributes and population-level relationships.

Furthermore, the dimensionality reduction from 30 variables to six clinically relevant indicators offers substantial advantages for Explainable Artificial Intelligence (XAI). The smaller feature space improves model transparency and facilitates interpretation using methods such as SHAP, LIME, and attention-based attribution techniques. Consequently, healthcare professionals can more readily understand the rationale behind automated predictions, thereby increasing trust and supporting clinical adoption of AI-driven decision-support systems.

Specifically, the novelty of this work lies in the systematic integration of multiple metaheuristic optimization algorithms, namely GA, PSO, and HHO, with deep learning models to improve diagnostic performance. Unlike previous studies that typically employ a single optimization strategy, our approach provides a comprehensive comparative analysis of different metaheuristic techniques for optimizing deep learning architectures and hyperparameters within the same experimental framework. This enables a more thorough investigation of the strengths and limitations of each optimization method and their impact on classification accuracy, robustness, and computational efficiency. Furthermore, the study demonstrates the effectiveness of the proposed hybrid optimization–deep learning framework in improving predictive performance, thereby contributing both methodological insights and practical value for intelligent healthcare applications verified by real data shown in **Table 7**.

4.6. Generalizability and external validation considerations

While the proposed HHO-based feature optimization framework achieved promising predictive performance, the generalizability of the identified feature subsets warrants further investigation. The current dataset was collected from university staff members and volunteers participating in AWVs in Ho Chi Minh City, Vietnam. Consequently, the selected features including ECG, Internal Medicine assessment (NoiKhoa), HGB, MCV, PCT, and MONO1 may partially reflect the demographic characteristics, disease prevalence patterns, lifestyle factors, and healthcare practices specific to this population.

Healthcare datasets often exhibit substantial variations across geographic regions, ethnic groups, age distributions, socioeconomic condi-

tions, and clinical protocols. Therefore, the relative importance of individual clinical variables may differ when the proposed framework is applied to populations with distinct epidemiological profiles. For example, hematological indicators that are highly informative in one population may have reduced predictive value in regions characterized by different nutritional status, chronic disease prevalence, or healthcare access patterns.

To establish broader clinical applicability, future studies should perform external validation using independent datasets collected from diverse geographic regions and demographic groups. Multi-center evaluations involving hospitals, community health programs, and wellness screening initiatives across different countries would provide a more comprehensive assessment of the robustness and transferability of the selected feature subset.

If the six identified features consistently demonstrate strong predictive performance across independent cohorts, they may serve as a candidate minimal screening panel for AWVs assessment, providing cost-effective and interpretable health risk evaluation. Conversely, if population-specific differences emerge, the proposed methodology itself remains broadly applicable. In such cases, the HHO-based feature optimization process and CBL-based evaluation framework can be re-applied to local healthcare datasets to identify region-specific optimal feature subsets while preserving the advantages of dimensionality reduction and model interpretability.

These observations highlight an important distinction between the generalizability of the selected features and the generalizability of the optimization methodology. Although the specific feature subsets may require validation across populations, the proposed optimization framework provides a systematic and transferable approach for discovering clinically relevant feature combinations in heterogeneous healthcare environments.

5. Discussion and limitations

AWVs programs have become increasingly important in preventive healthcare because they provide comprehensive assessments of an individual’s health status and facilitate the early detection of potential diseases. However, AWVs datasets typically contain a large number of heterogeneous features collected from demographic information, physical examinations, laboratory tests, and diagnostic imaging procedures. Identifying the most informative attributes is therefore essential for improving prediction performance while reducing the complexity and cost of healthcare screening.

The experimental results demonstrate that the proposed metaheuristic feature selection framework is highly effective in reducing feature dimensionality while maintaining strong predictive performance. Across the AWWs datasets collected from 2022 to 2025, the optimization algorithms successfully reduced the number of input features from 53 to as few as 10–16 features, depending on the dataset year. The selected features consistently included clinically meaningful indicators such as chest X-ray findings, electrocardiography (ECG), body weight, internal medicine examinations, ENT examinations, creatinine, HBsAg, blood pressure, and lipid-related biomarkers, highlighting their importance in health outcome prediction.

Among the investigated optimization methods, HHO demonstrated highly competitive performance by identifying compact feature subsets while achieving classification accuracies exceeding 94% on recent datasets. The combination of optimized feature subsets with convolution-based bidirectional learning models further improved predictive capability. In particular, the deep learning architectures effectively captured complex nonlinear relationships among clinical and laboratory variables, resulting in robust classification performance across multiple years of AWWs data. From a practical healthcare perspective, reducing the number of required examinations may significantly decrease screening costs, shorten examination time, and improve resource utilization. The proposed structure therefore provides valuable support for intelligent healthcare systems, enabling medical institutions to prioritize the most informative tests while maintaining reliable prediction performance. Despite these promising results, several limitations should be acknowledged. Future research should focus on validating the proposed framework using larger multi-center datasets, investigating advanced class-imbalance handling strategies, and integrating explainable artificial intelligence techniques to improve interpretability. These directions are consistent with current trends in healthcare data analytics, which emphasize scalable predictive modeling and intelligent clinical decision-support systems.⁵² First, the class distributions in some yearly datasets were highly imbalanced, which affected the prediction performance of minority classes and occasionally resulted in lower recall values. Second, although the combined datasets contain 2,518 records, individual yearly datasets remain relatively limited in size compared with large-scale healthcare repositories. Consequently, the generalizability of the developed models to different

populations, healthcare systems, or geographic regions requires further investigation. Another limitation is the computational cost associated with metaheuristic optimization. Although GA, PSO, and HHO effectively explore large feature spaces, their iterative search mechanisms increase computational requirements as dataset size and dimensionality grow. Furthermore, due to the stochastic nature of these algorithms, multiple independent runs may be necessary to ensure stable and reproducible results. Finally, while deep learning models achieve high predictive accuracy, their decision-making processes remain less interpretable than traditional machine learning approaches. Improving model explainability is particularly important in healthcare applications where clinical transparency and trust are essential. In addition, hybrid optimization approaches and parallel computing strategies may further reduce computational overhead and improve scalability for real-world healthcare applications.

The feature subsets identified through the metaheuristic optimization process provide a compact yet informative representation of AWWs records. Although the present study evaluates the effectiveness of this feature set using CBL-based architectures, the selected features are not restricted to these models. The optimized subset can be directly incorporated into more advanced healthcare analytics frameworks, including Transformer-based models, Temporal Fusion Transformers (TFT), Graph Neural Networks (GNNs), Explainable Boosting Machines (EBMs), and hybrid multimodal learning systems.⁵³ From a practical perspective, reducing the original feature space to six clinically relevant variables may improve computational efficiency, reduce model complexity, and improve interpretability while preserving predictive capability. Such advantages are particularly valuable for large-scale healthcare decision-support systems where model transparency and scalability are critical requirements. Future research may therefore investigate the effectiveness of the optimized feature subset within emerging deep learning and explainable artificial intelligence frameworks for healthcare prediction and risk stratification.

The optimized feature subsets identified in this study have potential applications beyond the CBL-based architectures evaluated herein. First, the selected features can serve as inputs to longitudinal patient trajectory prediction models, such as temporal attention networks and Transformer-based architectures, where the temporal evolution of ECG, Internal Medicine assessment, HGB,

MCV, PCT, and MONO1 across multiple AWWs can be modeled to identify disease progression patterns and future health risks. Such models are particularly suitable for capturing long-term dependencies and temporal interactions among clinical variables.

Second, the compact feature set may facilitate the development of Graph Neural Network (GNN)-based healthcare analytics frameworks. In such settings, patients can be represented as nodes within a similarity graph constructed from the six optimized features enabling the learning of population-level relationships and improving risk stratification, patient clustering, and disease surveillance. The reduced feature space simplifies graph construction and decreases computational complexity while preserving clinically relevant information.

Third, the selected features are well suited for integration with Explainable Artificial Intelligence (XAI) techniques, including SHAP, LIME, and attention-based interpretation methods. Because the model relies on only six clinically meaningful variables, explanations become more transparent and easier for healthcare professionals to interpret, thereby improving trust, accountability, and clinical adoption of AI-assisted decision-support systems.

Importantly, the dimensionality reduction achieved by the proposed metaheuristic optimization framework, from 30 original features to only six key indicators, offers significant advantages for advanced learning models. The compact representation reduces computational requirements, mitigates overfitting risks, improves model generalization, and enhances interpretability, making it particularly attractive for future healthcare analytics applications involving large-scale longitudinal and population-level datasets.

6. Conclusion

This study presented a hybrid machine learning framework for feature selection and predictive modeling using data from AWWs. Three metaheuristic optimization algorithms, namely GA, PSO, and HHO, were employed to identify informative feature subsets from a high-dimensional healthcare dataset. The selected features were subsequently utilized to train several machine learning classifiers and deep learning architectures for predictive analysis. Experimental results demonstrated that metaheuristic-based feature selection significantly reduced the dimensionality of the original dataset while preserving important predictive information. Among the investigated

optimization approaches, HHO produced competitive feature subsets and demonstrated strong performance in several evaluation scenarios. The obtained results indicate that feature selection can effectively improve model efficiency by eliminating redundant and less relevant variables. Furthermore, the deep learning models exhibited high training capabilities, achieving satisfactory training and validation performance on the AWWs dataset. The findings suggest that combining feature selection techniques with advanced predictive models can contribute to more accurate and computationally efficient healthcare analytics. In particular, the selected clinical and laboratory indicators provide valuable insights into the factors that may influence patient health outcomes and support data-driven decision-making in preventive healthcare. Despite these promising results, several limitations should be acknowledged. The study was conducted using a single AWWs dataset, which may limit the generalizability of the findings across different populations and healthcare environments. In addition, this work primarily focused on traditional machine learning classifiers and recurrent neural network architectures. Future research may investigate transformer-based models, explainable artificial intelligence techniques, and multi-center healthcare datasets to further improve prediction accuracy, interpretability, and robustness. Overall, the proposed framework demonstrates the potential of integrating metaheuristic feature selection with machine learning and deep learning methods for healthcare prediction tasks. The results provide a useful foundation for developing intelligent clinical decision-support systems capable of handling large-scale healthcare data while maintaining predictive effectiveness and computational efficiency.

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Conflict of interest

The authors confirm that there are no conflict of interest.

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Availability of data

The data utilized in this study were previously used and approved for research purposes in.¹ In accordance with the original data-use agreement and confidentiality requirements, the dataset is not publicly available and cannot be shared with third parties.

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