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Comparing PSO and ACO for XGBoost Heart Rate Classification in IoT Monitoring

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Abstract

Advances in Internet of Things (IoT) technology have transformed health monitoring systems, making them more adaptive and capable of acquiring real-time data. Heart rate, measured in beats per minute (BPM), is an important indicator of health status; however, BPM data generated by IoT devices is generally presented as numerical values without automatic classification of normal or abnormal conditions. This study aims to develop an IoT-based heart rate pattern classification system using the Extreme Gradient Boosting (XGBoost) algorithm, optimized with two metaheuristic algorithms Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), and to compare their performance characteristics. The study employs a quantitative experimental approach, beginning with real-time BPM data acquisition using a MAX30102 sensor and an ESP32-C3 Mini microcontroller from 40 participants, followed by data preprocessing, the development of an XGBoost model, parameter optimization using PSO and ACO, and model performance evaluation. The results show that both algorithms deliver equally good classification performance. PSO successfully identified an optimal threshold range of 68.44–97.82 BPM with an inference complexity of O(1), making it very fast during the prediction stage, while ACO excelled in training convergence speed and feature reduction effectiveness by using only 30% of the total features. The main contribution of this research is a comprehensive comparative analysis of the characteristics of PSO and ACO in terms of computational efficiency, optimization speed, inference complexity, and feature selection effectiveness, resulting in recommendations for selecting the appropriate optimization method to meet the implementation needs of IoT-based health monitoring systems, whether for real-time devices or cloud-based systems.

Keywords: *ant colony optimization, heart rate classification, internet* of things, *particle swarm optimization, XGBoost.*

1 Introduction

Advances in Internet of Things (IoT) technology have driven the transformation toward smarter health monitoring systems[1]. This technology is more adaptive and capable of acquiring real-time data. Various wearable devices equipped with biometric sensors enable the continuous gathering of physiological data. This supports the monitoring of health conditions without the necessity of attending a medical facility. One physiological parameter widely used as a health indicator is cardiovascular status, as measured by heart rate or beats per minute (BPM) [2], [3]. BPM values can provide information about physical condition, activity levels, or an early indication of heart problems if there are deviations from normal patterns. Although the data acquisition process using IoT technology has advanced rapidly, the main issue still concerns limitations in providing accurate decisions. For example, heart rate data exhibits characteristic fluctuations influenced by user activity and other physiological conditions. Existing heart rate data are generally presented as numerical values, while user conditions are rarely classified automatically as normal or abnormal.

Extreme Gradient Boosting (XGBoost) is a machine learning algorithm based on gradient boosting decision trees [4]. This algorithm has been widely applied because it offers high classification accuracy, handles complex data, and reduces the risk of overfitting. However, XGBoost's performance is also heavily affected by parameter configuration. The proper parameters generate the best model, whereas bias parameters produce the worst model. Therefore, parameter optimization is critical to the XGBoost for obtaining the best model.

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Various studies have utilized metaheuristic algorithms as approaches for parameter optimization and feature selection in machine learning algorithms [5]. Particle Swarm Optimization (PSO) is known as a metaheuristic algorithm which has the ability to explore global solutions, low computational complexity, and effective in determining the best parameter combinations [6]. On the other hand, Ant Colony Optimization (ACO) offers advantages in the feature selection process through a pheromone trail mechanism [7]. It enables identification of the most representative attributes. Both algorithms have been widely applied, offering their respective strengths. However, few studies have compared their performance, particularly when integrated with IoT for heart rate pattern identification.

This study integrates an IoT device equipped to identify heartbeat patterns. The identification process uses the XGBoost, which is optimized using two metaheuristic algorithms: PSO and ACO. The IoT device integrates a MAX30102 sensor and an ESP32-C3 Mini microcontroller to acquire BPM data in real time. Subsequently, preprocessing, feature extraction, model optimization, and performance evaluation were conducted using the metrics accuracy, precision, recall, and F1-score.

The main contribution of this study was the comparative analysis of the characteristics of the two metaheuristic algorithms in improving the performance of IoT for heart rate classification. In addition to evaluating the models' accuracy, this study also compared computational efficiency, optimization speed, inference complexity, and feature selection effectiveness, thereby providing recommendations for selecting optimization methods tailored to the implementation needs of IoT health monitoring systems.

2 Literature Review

IoT in healthcare has evolved significantly to support sensor-based health monitoring systems[3]. Various studies have developed BPM monitoring systems by integrating the MAX30102 sensor with the ESP32 microcontroller. This device is well-known for its low cost[2]. These IoT devices can generate real-time BPM with sufficient accuracy. However, most research still focuses on data acquisition and visualization. Meanwhile, intelligent analysis of BPM data remains limited, particularly in the automatic distinction between normal and abnormal heart rate patterns.

Meanwhile, machine learning algorithms have been widely applied to identify heart rate patterns. XGBoost is an enhanced algorithm based on gradient boosting decision trees[4]. It can efficiently generate boosted trees and operates in parallel. The XGBoost algorithm outperforms conventional classification algorithms in various medical classification cases [8], [9], [10]. It is effective in addressing nonlinear relationships between features and complex data distributions. However, XGBoost's performance is sensitive to hyperparameter configuration[11]. Default parameter settings often produce unsatisfactory models due to the unique characteristics of each dataset. Consequently, numerous studies have begun utilizing metaheuristic algorithms for parameter optimization.

PSO and ACO are metaheuristic algorithms widely used for optimizing machine learning model parameters. The PSO works based on the social behavior of swarms in finding the optimal position through an iterative mechanism of updating particle positions and velocities[12]. The main advantages of PSO lie in its ability to quickly find global solutions, its simple set of parameters, and its low computational cost[9]. Various studies have shown that the application of PSO can improve model accuracy and accelerate the convergence process[8], [9], [10]. Meanwhile, ACO mimics the behavior of ant colonies in finding the best path through the mechanism of forming and updating pheromone trails[13]. ACO is also widely applied in data optimization processes, particularly in feature selection. ACO can identify the most relevant features, thereby reducing model complexity without significantly compromising predictive power [14], [15]. Feature reduction also offers the benefits of shorter model training times and more efficient use of computational resources.

Several previous studies have combined the XGBoost with both ACO and PSO. The majority of these studies show improved model performance following optimization[7], [8], [9]. However, most studies have evaluated only a single optimization algorithm, thus failing to provide a comprehensive picture of the characteristics of each method. Another limitation of previous research is the lack of simultaneous integration of the model with IoT. Ideally, an IoT for health monitoring system should function as a unified whole, with data acquisition and analysis integrated rather than separated (Figure 1).

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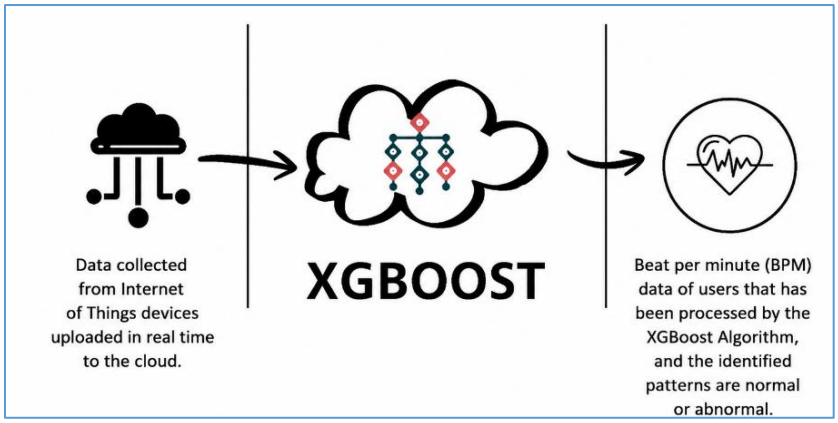


Figure 1 IoT for health monitoring system using XGBoost

Based on an analysis of the aforementioned prior research, there remains a research gap in the form of the absence of a comprehensive study comparing the performance of PSO and ACO on the XGBoost in IoT for heart rate pattern classification. Therefore, this study proposes a comparative approach using XGBoost as the primary classification model, which is then optimized using PSO and ACO. Additionally, this study acquires BPM data from deployed sensors. This approach is expected to provide a scientific contribution in the form of recommendations for selecting the most appropriate optimization method based on the characteristics of the implementation environment.

3 Research Method

This study used an experimental quantitative approach to evaluate the performance of optimization algorithms in improving heart rate pattern classification capabilities. The research flowchart is shown in Figure 2. This study was organized systematically, beginning with data acquisition using IoT devices. The obtained data is processed through preprocessing steps to produce a dataset. Then, this extracts relevant features for model development. There are three scenarios: deploy model using XGBoost without optimization and model optimization using metaheuristic algorithms. Finally, model performance was evaluated based on several evaluation metrics.

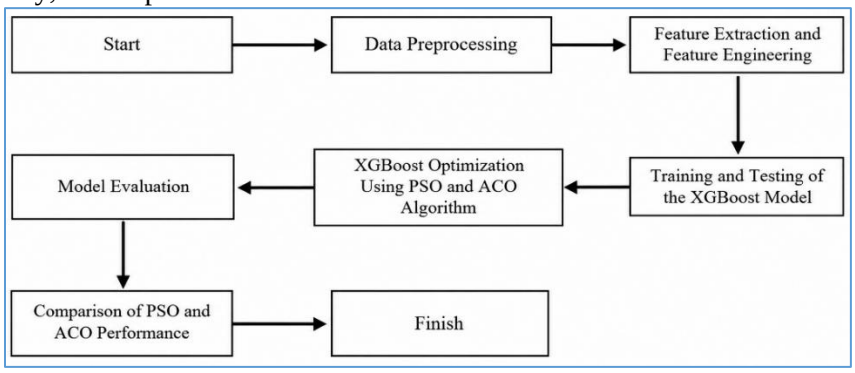


Figure 2 Research workflow

3.1 IoT Device Configuration

This study employed an IoT which consist two main components: the ESP32-C3 Mini as the system controller and the MAX30102 sensor as the heart rate data acquisition device. Figure 3 illustrates the IoT device configuration. The ESP32-C3 Mini was selected because it offers adequate computational capabilities [16] and supports Wi-Fi communication with relatively low power consumption [17]. Meanwhile, the MAX30102 was used because of its ability to provide real-time heart rate readings with a high level of stability[2].

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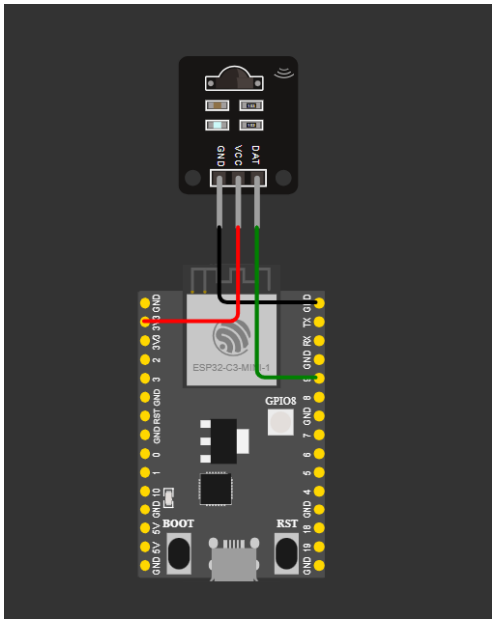


Figure 3 Illustration of ESP32-C3 mini and MAX30102 sensor integration

3.2 Data Acquisition

Heart rate data (beats per minute/BPM) was obtained in real time from IoT on measurements from 40 respondents. During the measurement process, the information was transmitted via a wireless network to a storage medium and recorded continuously, forming a time-series dataset. The dataset used was formatted in JSON, with each entry containing a timestamp attribute indicating the time of data collection and BPM as the sensor reading. Before being used in the analysis phase, the data underwent a preprocessing stage that included checking for and removing invalid or anomalous data, normalizing the dataset structure, and sorting the data based on measurement time to reduce the impact of noise and ensure the consistency, quality, and reliability of the data as the primary source for this research. This heart rate measurement dataset was recorded by the devices over a period of 300 seconds. The data includes metadata (Table 1) such as age, gender, data collection location, and measurement timestamps. Every second, the system records four main attributes: BPM value, condition classification (normal/abnormal), confidence, and time index (seconds).

Table 1 Heart rate measurement metadata

Fitur	Descriptions
Gender	Gender of respondent
Age	Age of respondent
Device ID	Id of respondent
Measurement duration	300 seconds
Timestamp	2025-11-29 10:54:50 (UTC)
BPM	beats per minute

3.3 Model Development

This study applied XGBoost to identify BPM conditions. The algorithm is essentially an ensemble method based on gradient boosting trees. In the initial stage, the XGBoost was built using default parameter configurations to produce a baseline model. This baseline model was then used as a benchmark against models that had undergone optimization using a metaheuristic algorithm.

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Algorithm XGBoost$(I, L, K, \eta, \lambda, \gamma)$

Input:

I: a training set $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$ with feature dimension m
$L(y, \hat{y})$: a differentiable loss function
K: number of boosting iterations
η: the learning rate
λ: regularization coefficient
γ: minimum loss reduction required for a split

1: Initialize the model with a constant value:

$$F_0(\mathbf{x}) = \underset{\gamma}{\operatorname{argmin}} \sum_{i=1}^{n} L(y_i, \gamma)$$

2: **for** $k = 1$ to K **do**:
3: /* Compute the sum of gradients and Hessians of all the samples */
4: $G \leftarrow \sum_{i \in I} \frac{\partial L(y_i, F_{k-1}(\mathbf{x}_i))}{\partial F_{k-1}(\mathbf{x}_i)}$
5: $H \leftarrow \sum_{i \in I} \frac{\partial^2 L(y_i, F_{k-1}(\mathbf{x}_i))}{\partial F_{k-1}(\mathbf{x}_i)^2}$
6: $T \leftarrow$ Build-Tree(I, G, H)
7: Let the terminal regions of T be R_j for $j = 1, ..., J_k$
8: For $j = 1, ..., J_k$ compute:

$$w_j = -\frac{G_j}{H_j + \lambda}$$

where G_j and H_j are the sum of gradients and Hessians at leaf node j.
9: Update the model:

$$F_k(\mathbf{x}) = F_{k-1}(\mathbf{x}) + \eta \sum_{j=1}^{J_k} w_j \mathbb{1}\{\mathbf{x} \in R_j\}$$

10: Output the final ensemble $F_K(\mathbf{x})$

3.4 Optimization using Metaheuristic Algorithm

This study applied ACO and PSO to optimized parameters on XGBoost algorithm. Both metaheuristic algorithms were applied separately (Figure 4). Thus, the combination of algorithms provides a model for identifying BPM conditions. Neither algorithm searches for an optimal solution through pheromone update mechanisms or particle position updates. The best results from both methods were compared to obtain the model with the most optimal classification performance. The resulting model is then used to classify BPM conditions into predetermined categories based on heart rate patterns obtained from sensor data.

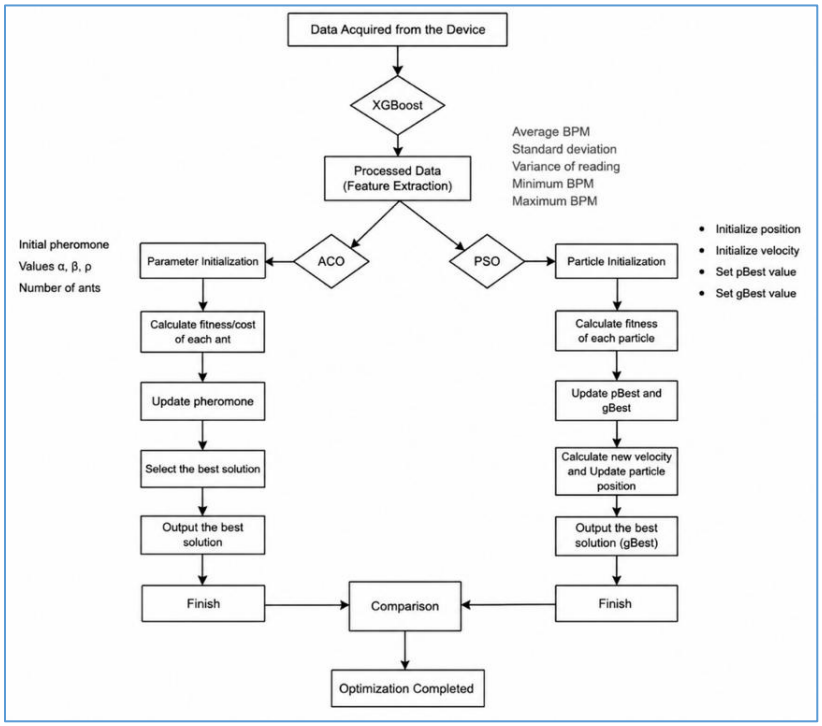


Figure 4 Flowchart for parameter optimization of metaheuristic algorithms

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3.5 Evaluation

The evaluation process was conducted to compare the performance of PSO and ACO on the XGBoost model for classifying BPM conditions. The evaluation was based on the metrics of Accuracy, Precision, Recall, and F1-Score. In addition to these metrics, this study also evaluated the characteristics of the two optimization algorithms in terms of convergence speed, computational efficiency, inference complexity, and feature reduction capabilities. This analysis was conducted to provide a more comprehensive overview of the strengths and limitations of each algorithm when implemented in an IoT for health monitoring system.

4 Results and Analysis

4.1 Brief Dataset

The IoT successfully acquired BPM data from 40 individuals: 38 were classified as normal and 2 as abnormal. Each individual had 300 seconds of recorded BPM data. Table 2 presents a summary of the dataset used to analyze the performance of the PSO and ACO algorithms.

Table 2 Dataset statistical summary

Parameters	Value
Baseline BPM	81.24
Mean BPM	83.21
Standard Deviation	11.15
BPM Minimum	69
BPM Maximum	124
Abnormal percentage	6.33%

4.2 Comparative Analysis Based on Quantitative Metrics

This section presents and analyzes the performance of the PSO and ACO algorithms based on quantitative metrics. The classification results of PSO and ACO for 40 samples are presented in the confusion matrix in Figure 5. Both algorithms show identical results: 38 normal samples were correctly predicted, and 2 abnormal samples were also correctly predicted. This means that the accuracy, precision, recall, and F1 score for both models are 100%. In other words, both metaheuristic algorithms perform equally well. Both algorithms have their respective methods for generating the best model. PSO successfully identified an optimal threshold range of 68.44 - 97.82 BPM as the boundary between normal and abnormal conditions. This parameter produced a classification model with stable performance across the entire test dataset. ACO was applied to perform feature selection so that only the most relevant attributes were used in the classification process.

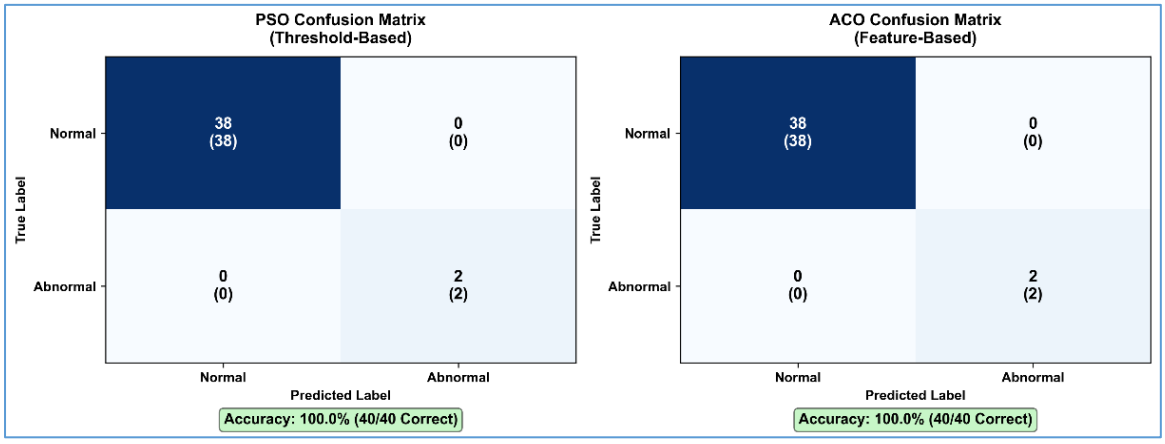


Figure 5 Confusion matrix of the PSO and ACO algorithms

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4.3 Comparative Analysis Based on Computational Time

This study also analyzed the computational time of the algorithms. Two aspects were of particular interest: convergence speed and inference speed. Convergence speed relates to the duration of the model-building process, while inference speed represents the time required for a trained model to process new data. Figure 6 presents a comparison of the two algorithms in terms of model-building. The PSO convergence curve moves gradually, rising slowly until it reaches an optimal point at around 100 iterations. In contrast, the ACO curve rises sharply and reaches its best condition within just the first five iterations. We can immediately see that ACO is 10–20 times faster during the training process. ACO reaches optimal conditions much faster and is more efficient than PSO.

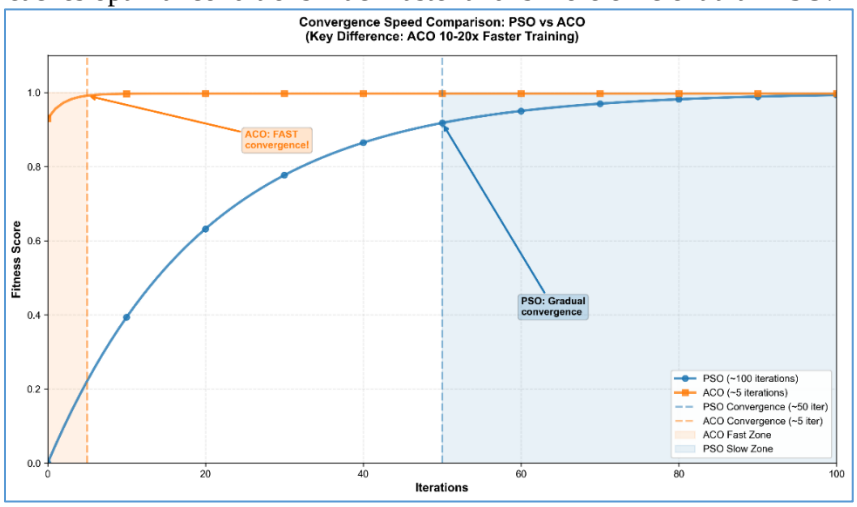


Figure 6 Comparison of PSO and ACO training speeds

It is the characteristics of ACO that make it faster and more efficient for generating models. ACO reduces the number of features and provides significant benefits to the computing environment. Reducing the number of features speeds up the model training process while reducing the demand for computing resources. This statement is supported by the reduced number of features (Figure 7). ACO uses only 30 percent of the features, whereas PSO uses all of them. This feature reduction decreases the model's complexity without compromising its classification ability. Even though it uses only 30 percent of the total features, the model still achieves classification performance on par with PSO.

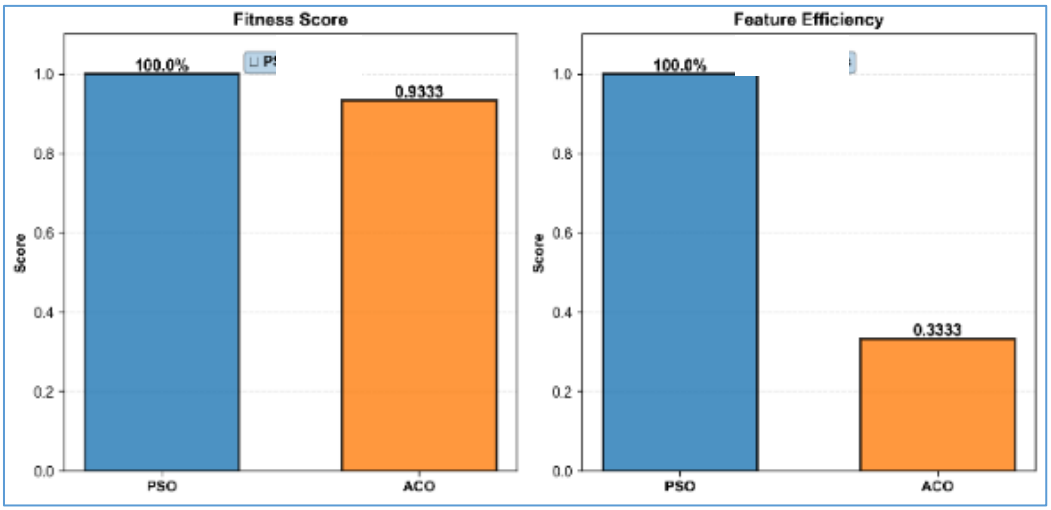


Figure 7 Feature selection results

The inference time aspect shows the opposite situation. ACO is fast during training, whereas PSO is exceptionally fast during inference. Figure 8 illustrates the inference time and computational complexity of the two metaheuristic algorithms. PSO requires only two simple threshold operations

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(O(1)), while ACO requires calculations on five selected features (O(5)). Furthermore, PSO is 10 times faster than ACO at predicting new datasets in a real-time system.

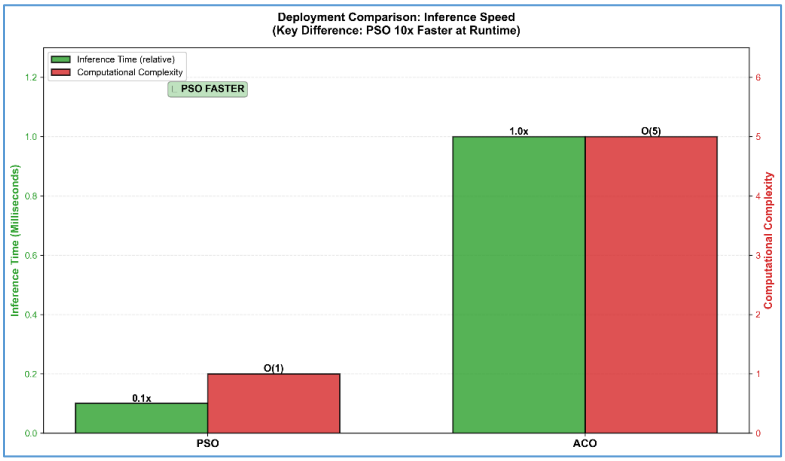


Figure 8 Inference speed comparison

4.4 Comparative Analysis Based on Other Metric

To provide a comprehensive overview, this study not only evaluates the algorithms based on quantitative metrics or computational time, but also compares their operational characteristics. Figure 9 visualizes the "characteristic curves" of the two algorithms. The figure shows the performance characteristics of PSO and ACO based on seven evaluation criteria: accuracy, training speed, deployment speed, simplicity, efficiency, robustness, and scalability. In general, PSO has advantages in deployment speed, algorithmic simplicity, robustness, and efficiency, making it more suitable for optimization processes that require fast convergence and relatively simple implementation. Conversely, ACO demonstrates better performance in training speed and scalability, while maintaining a high and stable level of accuracy. These comparison results show that the two algorithms have complementary strengths.

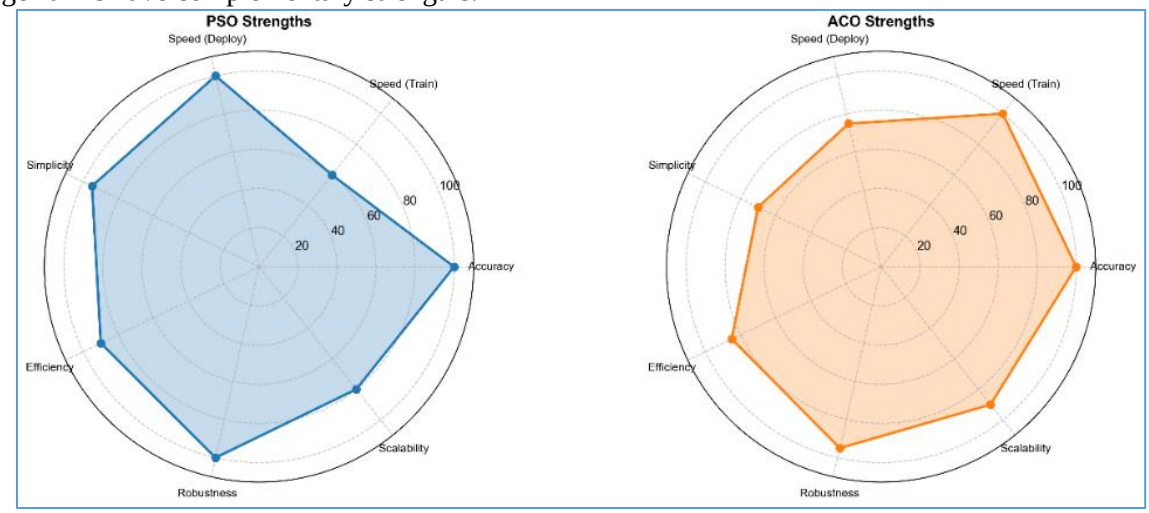


Figure 9 Comprehensive performance characteristics based on seven metrics

5 Conclusion

This study successfully acquired BPM data from 40 respondents using IoT devices. The data was processed using XGBoost and optimized with the PSO and ACO optimization algorithms. Both algorithms exhibit equally good quantitative performance. In addition, each algorithm has distinct operational advantages. PSO is capable of finding the optimal threshold within the range of 68.44–97.82 BPM and provides very high inference speed thanks to its O(1) complexity, making it ideal for IoT devices and real-time monitoring systems. Conversely, ACO excelled in the training process with fast convergence and effectiveness in feature reduction, making it more suitable for cloud-based

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systems and environments with greater computational capacity. Furthermore, an analysis of the differences in the characteristics of the two algorithms provides clear guidance on method selection based on application needs. The approach developed in this study can serve as a foundation for implementing faster, more efficient early-detection systems for cardiovascular issues that can be adapted to various use cases.

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References

[1] E. A. Nugroho, R. Herlambang, J. Juhaeriyah, and R. Wulandari, "*Design and Development of Smart Bracelet System for Heart Health Monitoring Based on Internet of Things (IoT)*," *Malaysian Journal of Science and Advanced Technology*, 2024, DOI: 10.56532/mjsat.v4i3.341.

[2] N. Andriani, A. Siswanto, M. F. Mohd Fuzi, R. A. JM Gining, and N. Mohd Noor, "*Monitoring System for Heart Rate, Blood Oxygen Level, and Body Temperature using MAX30102 Sensor based on Internet of Things*," *Int. J. SCI. Res.*, Vol. 4, No. 2, 2025, DOI: 10.25299/ijsr.2024.23687.

[3] W. Panjaitan, J. Jend Yani, K. Naga, and K. Kisaran Timur, "Sistem Monitoring Detak Jantung menggunakan *Pulse Heart Rate* Sensor dan Nodemcu," *Jurnal Riset Sistem Informasi dan Teknik Informatika*, Vol. 3, 2025.

[4] I. M. K. Karo, "Implementasi Metode *XGBoost* dan *Feature Importance* untuk Klasifikasi pada Kebakaran Hutan dan Lahan," *Journal of Software Engineering, Information and Communication Technology*, Vol. 1, No. 1, pp. 10–16, 2020.

[5] M. Saber, A. A. Abdelhamid, and A. Ibrahim, "*Metaheuristic Optimization Review: Algorithms and Applications*," *Journal of Artificial Intelligence and Metaheuristics*, Vol. 3, No. 1, 2023, DOI: 10.54216/jaim.030102.

[6] A. Salsabila, Y. M. Rangkuti, I. M. K. Karo, and S. I. Al-Idrus, "*Determining Tourist Destination Priorities using Website-based Particle Swarm Optimization Methods (Case Study : North Padang Lawas Regency)*," *Journal of Mathematics, Computations and Statistics*, Vol. 7, No. 2, 2024, DOI: 10.35580/jmathcos.v7i2.4233.

[7] A. Y. Krishna, K. R. Kiran, N. R. Sai, A. Sharma, S. P. Praveen, and J. Pandey, "*Ant Colony Optimized XGBoost for Early Diabetes Detection: A Hybrid Approach in Machine Learning*," *Journal of Intelligent Systems and Internet of Things*, Vol. 10, No. 2, 2023, DOI: 10.54216/JISIoT.100207.

[8] J. Yi, P. Yu, T. Huang, and Z. Xu, "*Optimization of Transformer Heart Disease Prediction Model based on Particle Swarm Optimization Algorithm*," in *2024 6th International Conference on Frontier Technologies of Information and Computer, ICFTIC 2024*, 2024. DOI: 10.1109/ICFTIC64248.2024.10913096.

[9] K. Cao *et al.*, "*Prediction of Cardiovascular Disease based on Multiple Feature Selection and Improved PSO-XGBoost Model*," *SCI. Rep.*, Vol. 15, No. 1, 2025, DOI: 10.1038/s41598-025-96520-7.

[10] D. A. Dias Júnior *et al.*, "*Automatic Method for Classifying COVID-19 Patients based on Chest X-Ray Images, using Deep Features and PSO-Optimized XGBoost*," *Expert Syst. Appl.*, Vol. 183, 2021, DOI: 10.1016/j.eswa.2021.115452.

[11] D. N. Jawza, M. I. Mazdadi, A. Farmadi, T. H. Saragih, D. Kartini, and V. Abdullayev, "*Enhancing Diabetes Prediction Accuracy using Random Forest and XGBoost with PSO and GA-Based Feature Selection*," *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, Vol. 7, No. 2, 2025, DOI: 10.35882/jeeemi.v7i2.626.

[12] D. T. Nigatu, T. Gemechu Dinka, and S. Luleseged Tilahun, "*Convergence Analysis of Particle Swarm Optimization Algorithms for Different Constriction Factors*," *Front. Appl. Math. Stat.*, Vol. 10, 2024, DOI: 10.3389/fams.2024.1304268.

[13] C. Wang, S. Zhang, T. Ma, Y. Xiao, M. Z. Chen, and l. Wang, "*Swarm Intelligence: A Survey of Model Classification and Applications*," 2025. DOI: 10.1016/j.cja.2024.03.019.

[14] S. Kanagaraj, M. S. Hema, and M. N. Guptha, "*Optimized Supervised Learning Approach to Predict Parkinson's Disease with Minimal Attributes using PPMI Datasets*," *Multimed. Tools Appl.*, Vol. 83, No. 16, 2024, DOI: 10.1007/s11042-023-17582-1.

[15] S. Kaliraj, V. G. P. Sahasranth, and V. Sivakumar, "*Generalization of Set of Features for the Software Fault Prediction using Ant Colony-based Feature Selection*," *International Journal of Information Technology (Singapore)*, 2025, DOI: 10.1007/s41870-025-02919-w.

[16] N. K. Upadhyay, P. Sudhakar, and V. Kumar, "*Efficient Cryptographic Configurations and Lightweight Communication Protocols for Secure Smart Home Systems*," in *2025 3rd International Conference on Communication, Security, and Artificial Intelligence, ICCSAI 2025*, 2025. DOI: 10.1109/ICCSAI64074.2025.11063770.

[17] V. Jennifer and K. Balamurugan, "*IoT Driven Hybrid Locator*," in *Proceedings of the 6th International Conference on Electronics and Sustainable Communication Systems, ICESC 2025*, 2025. DOI: 10.1109/ICESC65114.2025.11212387.