FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 14, June, 2026, pp 304 – 309
DOI: https://doi.org/10.33003/fjs-2026-1014-5414

Optimization Algorithms in Biometric Recognition Systems: A Systematic Review and Comparative Analysis

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ABSTRACT
Biometric recognition systems have become an integral component of modern authentication due to their ability to provide secure and reliable identity verification across applications including banking, healthcare, border control, forensic investigations, and national identity management. As biometric systems increasingly rely on high-dimensional feature representations generated by conventional feature extraction methods and deep learning models, efficient optimization techniques have become essential for improving recognition performance while reducing computational cost. This study presents a systematic review and comparative analysis of optimization algorithms applied to biometric recognition systems published between 2020 and 2026. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, relevant studies were retrieved from Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, Wiley Online Library, and Google Scholar. The selected studies were evaluated according to optimization technique, biometric modality, recognition accuracy, feature reduction capability, convergence speed, computational complexity, robustness, and scalability. The review shows that optimization algorithms substantially enhance biometric recognition by improving feature selection, reducing feature dimensionality, optimizing classifier performance, and facilitating multimodal biometric fusion. Comparative analysis indicates that recent bio-inspired algorithms, particularly the Whale Optimization Algorithm (WOA) and Grey Wolf Optimizer (GWO), consistently achieve superior performance in terms of recognition accuracy, convergence behavior, and scalability across multiple biometric modalities. The review further identifies emerging research directions involving optimization-assisted deep learning, hybrid optimization frameworks, explainable artificial intelligence, and multimodal biometric systems, while highlighting key challenges and opportunities for future research.

Received: 01 Jul. 2026
Accepted: 14 Aug. 2026
Published: 26 Aug. 2026

Keywords: Biometrics; Optimization Algorithms; Feature Selection; Multimodal Biometrics; Fingerprint Recognition; Finger Knuckle Print; Whale Optimization Algorithm

INTRODUCTION

Biometric recognition systems have become one of the most effective approaches for automatic identity verification by utilizing unique physiological and behavioural characteristics that are difficult to duplicate or transfer. Compared with conventional authentication methods such as passwords, personal identification numbers (PINs), and smart cards, biometric technologies provide enhanced security, convenience, and accountability, making them increasingly important in banking, healthcare, border control, law enforcement, mobile authentication, forensic investigations, and national identity management (Jain et al., 2024).

A wide range of biometric modalities has been investigated, including fingerprint, finger knuckle print (FKP), face, iris, palmprint, voice, gait, and handwritten signature. Among these, fingerprint recognition remains one of the most widely deployed biometric modalities because of its uniqueness, permanence, and mature acquisition technology (Ji et al., 2025). Recent research has continued to demonstrate the practical relevance of fingerprint biometrics in real-world authentication applications. For example, Usiobaifo and Osaseri (2025) developed a mobile fingerprint attendance system for students and lecturers, demonstrating the continued applicability of fingerprint-based recognition for identity verification and access-related applications. Finger knuckle print recognition has also emerged as a promising complementary modality owing to its stable skin texture patterns and its ability to improve the robustness of multimodal biometric systems (Umar & Abiola, 2024).

Despite significant advances in biometric sensing and feature extraction, modern recognition systems frequently generate high-dimensional feature representations that contain redundant or irrelevant information. These characteristics increase computational complexity, storage requirements, processing time, and the likelihood of model overfitting, particularly when large biometric databases are involved. Consequently, effective feature selection and optimization have become essential for developing accurate, scalable, and computationally efficient biometric recognition systems (Fan et al., 2024; Yang et al., 2024).

To address these challenges, optimization algorithms have been widely incorporated into biometric recognition pipelines. Their applications include feature selection, dimensionality reduction, classifier parameter optimization, hyperparameter tuning, and multimodal biometric fusion. The application of optimization techniques to computational problems has also been reported by Obunadike et al. (2018) investigated the optimization of the K-mode algorithm using

Particle Swarm Optimization (PSO), demonstrating the application of population-based optimization to improve computational solutions. Such studies reinforce the broader relevance of optimization techniques for addressing complex computational problems. In biometric recognition, optimization algorithms can identify informative feature subsets and improve learning models, thereby enhancing recognition accuracy while reducing computational overhead. Numerous optimization techniques have been applied to biometric recognition, including Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Gravitational Search Algorithm (GSA), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA). The rapid development of bio-inspired and hybrid optimization methods, together with their integration into machine learning and deep learning architectures, has considerably expanded the range of optimization strategies available for biometric applications. These algorithms differ in their search mechanisms, convergence characteristics, computational requirements, exploration and exploitation capabilities, and suitability for high-dimensional biometric feature spaces.

Although previous studies have investigated individual optimization techniques or specific biometric modalities, the existing literature remains fragmented. Most reviews emphasize a limited set of algorithms or focus on a single biometric modality, making it difficult to obtain a comprehensive understanding of recent advances, comparative performance, and emerging research trends. In addition, the rapid evolution of optimization-assisted deep learning and hybrid optimization frameworks has created the need for an updated synthesis of current evidence. There is therefore a need for a systematic examination of how different optimization algorithms have been employed across biometric modalities and how their performance compares under different experimental conditions.

This study addresses this gap by presenting a systematic review and comparative analysis of optimization algorithms applied to biometric recognition systems published between 2020 and 2026. Following the PRISMA 2020 guidelines, the review examines optimization methods across major biometric modalities and compares their performance with respect to recognition accuracy, feature reduction capability, convergence speed, computational complexity, robustness, and scalability. Particular attention is given to fingerprint, finger knuckle print, and multimodal biometric recognition because of their growing significance in secure authentication. The findings provide a comprehensive overview of current research, identify existing challenges, and outline promising directions for the development of next-generation optimization-driven biometric recognition systems.

Objectives of the Study

The objectives of this systematic review are to:

i. Identify the optimization algorithms most frequently employed in biometric recognition systems.
ii. Examine their applications in feature selection, dimensionality reduction, classifier optimization, and multimodal biometric fusion.
iii. Compare optimization algorithms based on recognition accuracy, convergence speed, computational complexity, robustness, and scalability.
iv. Evaluate the effectiveness of optimization techniques across major biometric modalities, particularly fingerprint, finger knuckle print, face, and iris recognition.
v. Identify current research gaps and emerging trends in optimization-driven biometric recognition.
vi. Recommend future research directions for developing accurate, efficient, and scalable biometric recognition systems.

MATERIALS AND METHODS

Review Design

This study employed a systematic literature review (SLR) to synthesize recent research on optimization algorithms in biometric recognition systems. The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure transparency, consistency, and reproducibility (Page et al., 2021).

Research Questions

The review was guided by the following research questions:

i. RQ1: Which optimization algorithms are most frequently applied in biometric recognition systems?
ii. RQ2: Which biometric modalities have benefited most from optimization-based approaches?
iii. RQ3: How do optimization algorithms influence feature selection, dimensionality reduction, and recognition accuracy?
iv. RQ4: Which optimization algorithms provide the best balance between recognition performance and computational efficiency?
v. RQ5: What research gaps and future research directions exist in optimization-driven biometric recognition?

Study Selection

The study selection process followed the four PRISMA stages: identification, screening, eligibility, and inclusion. The initial database search retrieved 1,178 records, of which 1,032 remained after duplicate removal. Following title and abstract screening, 210 full-text articles were assessed for eligibility, and studies meeting the predefined inclusion criteria were included in the qualitative synthesis.

Data Extraction and Quality Assessment

Data were extracted using a standardized extraction form that recorded publication year, biometric modality, optimization algorithm, application area, dataset, evaluation metrics, and principal findings. Study quality was assessed based on methodological rigor, experimental validation, dataset adequacy, and the reporting of performance indicators, including recognition accuracy, Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR), precision, recall, convergence speed, and computational complexity.

Data Synthesis

A qualitative comparative synthesis was performed to evaluate optimization algorithms across biometric applications. The selected studies were compared using six performance criteria: recognition accuracy, feature reduction capability, convergence speed, computational complexity, robustness, and scalability. The synthesis was used to identify the strengths, limitations, and emerging research trends of the reviewed optimization techniques.

Classification and Theoretical Foundations of Optimization Algorithms

Overview of Optimization Algorithms in Biometric Recognition

Optimization algorithms play an important role in biometric recognition by improving the efficiency of feature selection, parameter optimization, and learning models. Most approaches adopted in biometric applications are metaheuristic algorithms, which efficiently search complex, nonlinear solution spaces without requiring gradient information (Mirjalili& Lewis, 2016). Based on their underlying search mechanisms, the optimization algorithms reviewed in this study are classified into five categories: evolutionary algorithms, swarm intelligence algorithms, physics-based algorithms, bio-inspired algorithms, and hybrid optimization frameworks.

Optimization Algorithms
- Evolutionary (GA, DE)
- Swarm Intelligence (PSO, ACO, ABC, FA)
- Physics-Based (GSA)
- Bio-Inspired (GWO, WOA)
- Hybrid Frameworks (PSO-GA, GWO-SVM, WOA-CNN, WOA-Transformer)

Figure 1: Classification of Optimization Algorithms

RESULTS AND DISCUSSION

Evolutionary Algorithms

Evolutionary algorithms imitate the process of natural evolution to search for optimal solutions. The Genetic Algorithm (GA) and Differential Evolution (DE) are widely used because of their strong global search capabilities. GA is effective for combinational optimization but generally converges more slowly than DE, which offers faster convergence with moderate computational complexity (Kumar & Gupta, 2024).

Swarm Intelligence Algorithms

Swarm intelligence algorithms are inspired by the collective behavior of social organisms. Representative methods include Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and the Firefly Algorithm (FA). These algorithms are widely employed for feature and parameter optimization. PSO is known for rapid convergence, whereas ACO and ABC provide stronger exploration of the search space.

Physics-Based Algorithms

Physics-based optimization algorithms are derived from natural physical principles. The Gravitational Search Algorithm (GSA) models candidate solutions as interacting masses whose movements are governed by gravitational attraction. Although effective for parameter optimization, its computational cost increases as problem dimensionality grows.

Bio-Inspired Algorithms

Bio-inspired algorithms represent one of the most active areas of optimization research in biometrics. The Grey Wolf Optimizer (GWO) models the social hierarchy and hunting strategy of grey wolves, whereas the Whale Optimization Algorithm (WOA) is inspired by the bubble-net feeding behavior of humpback whales. Their balanced search strategies have made them effective for solving complex optimization problems, and recent studies report competitive performance across multiple biometric applications (Cao et al., 2024; Esfahani et al., 2025).

Hybrid Optimization Frameworks

Hybrid optimization frameworks integrate two or more complementary algorithms to improve search efficiency and solution quality. Common examples include PSO-GA, GWO-SVM, WOA-CNN, and WOA-Transformer, which combine global exploration with effective local refinement to enhance optimization and learning performance (Yang et al., 2024).

Comparative Characteristics of Optimization Algorithms

Table 1: Characteristics of Major Optimization Algorithms

Algorithm	Category	Major Strength	Main Limitation	Common Biometric Applications
GA	Evolutionary	Strong global search	Slow convergence	Feature selection, classifier tuning
DE	Evolutionary	Fast convergence	Moderate exploration	Continuous optimization
PSO	Swarm Intelligence	Simple and fast	Premature convergence	Feature selection, parameter optimization
ACO	Swarm Intelligence	Strong exploration	High computational cost	Pattern recognition
ABC	Swarm Intelligence	Good exploration	Moderate convergence	Feature optimization
FA	Swarm Intelligence	Effective local search	Scalability issues	Multimodal biometrics
GSA	Physics-Based	Strong exploitation	Slow convergence	Parameter optimization
GWO	Bio-Inspired	Balanced search strategy	Moderate computational cost	Feature selection, classification
WOA	Bio-Inspired	Fast convergence and balanced exploration–exploitation	Moderate complexity	Fingerprint, FKP, face, iris, multimodal biometrics

Summary

The reviewed optimization algorithms employ diverse search strategies to address complex optimization problems in biometric recognition. While each category has distinct strengths and limitations, recent bio-inspired and hybrid approaches have demonstrated improved search efficiency and adaptability, motivating their increasing adoption in modern biometric systems.

Applications of Optimization Algorithms in Biometric Recognition Systems

Optimization algorithms have been applied across a wide range of biometric modalities to improve recognition performance, computational efficiency, and system robustness.

Fingerprint and Finger Knuckle Print (FKP) Recognition
Fingerprint and Finger Knuckle Print (FKP) recognition have received considerable attention because of their complementary characteristics in unimodal and multimodal biometric systems. In fingerprint recognition, optimization algorithms are primarily used for feature selection, minutiae optimization, and classifier tuning to improve matching performance under noisy or partial-image conditions. For FKP recognition, optimization techniques are applied to features extracted using methods such as Gabor filters, Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and deep learning models. Algorithms including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) have been successfully employed to reduce feature dimensionality and improve classification accuracy. Hybrid models such as GWO-SVM and WOA-CNN further enhance recognition by jointly optimizing feature selection and classifier parameters (Cao et al., 2024; Yang et al., 2024).

Face, Iris, and Palmprint Recognition
Optimization algorithms have also been widely adopted in face, iris, and palmprint recognition. In face recognition, they are used to optimize deep features extracted by Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), improving recognition under variations in illumination, pose, and occlusion. For iris and palmprint recognition, optimization techniques support image segmentation, feature selection, template matching, and classifier optimization, resulting in improved recognition accuracy and lower Equal Error Rates (EER). Recent studies indicate that bio-inspired algorithms such as GWO and WOA perform particularly well in these applications (Esfahani et al., 2025).

Voice, Gait, and Multimodal Biometric Systems
In voice and gait recognition, optimization algorithms are employed for feature selection, noise reduction, temporal sequence optimization, and deep learning hyperparameter tuning. Techniques such as PSO, Artificial Bee Colony (ABC), and WOA have demonstrated improved performance in speaker identification and gait recognition, particularly under unconstrained conditions.
Optimization plays an even greater role in multimodal biometric systems by improving feature-level, score-level, and decision-level fusion. Hybrid optimization frameworks, including WOA-CNN, PSO-LSTM, and WOA-Transformer, have shown promising results by integrating metaheuristic optimization with deep learning, leading to higher recognition accuracy and more robust multimodal authentication systems (González-Soler et al., 2024).

Table 2. Applications of Optimization Algorithms across Biometric Modalities

Biometric Modality	Major Applications of Optimization	Frequently Used Algorithms
Fingerprint	Feature selection, minutiae optimization, classifier tuning	GA, PSO, GWO, WOA
Finger Knuckle Print	Texture feature selection, classifier optimization	GWO, PSO, WOA
Face	Deep feature selection, CNN hyperparameter optimization	PSO, GWO, WOA
Iris	Segmentation, feature optimization, template matching	GA, PSO, GWO, WOA
Palmprint	Feature reduction, classifier optimization	GA, PSO, GWO, WOA
Voice	MFCC optimization, speaker classification	PSO, ABC, WOA
Gait	Feature selection, sequence optimization	PSO, GWO, LSTM hybrids
Multimodal Biometrics	Feature fusion, score fusion, classifier optimization	WOA, GWO, PSO, Hybrid models

Comparative Analysis and Performance Evaluation of Optimization Algorithms
This section compares the optimization algorithms reviewed in this study based on six key performance criteria: recognition accuracy, feature reduction capability, convergence speed, computational complexity, scalability, and robustness. These criteria determine the suitability of optimization techniques for biometric feature selection, classifier optimization, and multimodal biometric fusion.

Performance Evaluation Criteria
The effectiveness of optimization algorithms was evaluated using the following criteria:

i. Recognition Accuracy: The ability to improve biometric identification and verification by selecting discriminative features.
ii. Feature Reduction Capability: The extent to which redundant and irrelevant features are removed while preserving classification performance.
iii. Convergence Speed: The number of iterations required to reach an optimal or near-optimal solution.
iv. Computational Complexity: The computational resources required during optimization.
v. Scalability: The ability to maintain performance with increasing dataset size and feature dimensionality.
vi. Robustness: The capability to produce stable solutions under noisy, high-dimensional, or varying data conditions.

Comparative Performance of Optimization Algorithms
Traditional optimization techniques such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO) have been widely applied in biometric feature selection because of their strong global search capabilities. However, both algorithms generally require higher computational resources and exhibit slower convergence, limiting their effectiveness in large-scale biometric systems.
Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) provide faster convergence and lower computational complexity, making them suitable for real-time biometric applications. Nevertheless, PSO may suffer from premature convergence when optimizing highly complex feature spaces.
Recent studies increasingly favor bio-inspired algorithms, particularly the Grey Wolf Optimizer (GWO) and the Whale Optimization Algorithm (WOA). These algorithms maintain an effective balance between exploration and exploitation, resulting in superior feature selection, faster convergence, and greater robustness. WOA consistently demonstrates high recognition accuracy and excellent scalability, making it particularly suitable for high-dimensional biometric datasets

and multimodal recognition systems (Cao et al., 2024; Esfahani et al., 2025).

Table 3: Comparative Performance of Optimization Algorithms

Algorithm	Recognition Accuracy	Feature Reduction	Convergence	Complexity	Scalability	Robustness
GA	High	High	Moderate	High	Moderate	High
DE	High	High	Fast	Moderate	High	High
PSO	High	Moderate	Fast	Low	High	Moderate
ACO	Moderate	High	Slow	High	Moderate	Moderate
ABC	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
FA	High	Moderate	Moderate	Moderate	Moderate	Moderate
GSA	Moderate	Moderate	Moderate	High	Moderate	Moderate
GWO	Very High	High	Fast	Moderate	High	Very High
WOA	Excellent	Excellent	Very Fast	Moderate	Excellent	Excellent

Performance in Fingerprint and Finger Knuckle Print Recognition

The reviewed literature demonstrates that optimization algorithms significantly improve the performance of fingerprint and finger knuckle print (FKP) recognition systems. PSO and GWO enhance feature selection and classifier tuning, while WOA consistently achieves superior feature reduction, faster convergence, and higher recognition accuracy. In multimodal fingerprint–FKP systems, WOA effectively manages large fused feature spaces, producing more discriminative feature subsets and reducing computational complexity.

Discussion

Algorithm performance depends on the biometric modality, dataset characteristics, and optimization objective. Traditional algorithms remain effective but generally converge more slowly than recent bio-inspired approaches. Overall, GWO and WOA provide the best balance between accuracy, convergence speed, robustness, and scalability, making them suitable for high-dimensional biometric recognition. Hybrid optimization with deep learning remains a promising research direction.

Research Gaps, Challenges, and Future Research Directions

Despite considerable progress in applying optimization algorithms to biometric recognition, several research gaps and practical challenges remain. Existing studies demonstrate that optimization techniques improve feature selection, dimensionality reduction, classifier tuning, and multimodal fusion. However, issues related to benchmarking, scalability, computational efficiency, explainability, and real-world deployment continue to limit their broader adoption.

Research Gaps and Challenges

The literature reveals four major gaps: (i) lack of standardized benchmarking frameworks, (ii) limited research on fingerprint–FKP multimodal systems, (iii) scarcity of large public datasets, and (iv) insufficient integration of optimization algorithms with deep learning and explainable AI. These limitations reduce reproducibility and hinder large-scale deployment.

Future Research Directions

Future work should emphasize hybrid optimization, optimization-assisted deep learning, explainable optimization, lightweight algorithms for edge devices, and large-scale fingerprint–FKP multimodal systems. These directions are expected to improve recognition accuracy, computational efficiency, and scalability.

CONCLUSION

This systematic review examined the application of optimization algorithms in biometric recognition systems published between 2020 and 2026, following the PRISMA 2020 methodology. The review demonstrates that optimization algorithms play a vital role in improving biometric recognition by enhancing feature selection, reducing dimensionality, optimizing classifier performance, and supporting multimodal biometric fusion. These improvements contribute to higher recognition accuracy, lower computational complexity, and greater scalability across diverse biometric applications.

The reviewed studies show that traditional optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Gravitational Search Algorithm (GSA) remain effective for feature selection and classifier optimization. However, recent bio-inspired algorithms, particularly the Grey Wolf Optimizer (GWO) and the Whale Optimization Algorithm (WOA), consistently achieve superior performance because of their balanced exploration–exploitation strategies, faster convergence, and robustness in high-dimensional search spaces. Among the reviewed techniques, WOA demonstrated the strongest overall performance across fingerprint, finger knuckle print (FKP), face, iris, and multimodal biometric recognition systems.

The review also identified several research gaps, including the lack of standardized benchmarking frameworks, limited studies on fingerprint–FKP multimodal systems, scarcity of large-scale public datasets, and insufficient integration of optimization algorithms with deep learning, transformer architectures, and explainable artificial intelligence. Addressing these limitations will improve the reproducibility, scalability, and practical deployment of optimization-driven biometric systems.

Future research should focus on hybrid and adaptive optimization frameworks, optimization-assisted deep learning, explainable optimization models, and lightweight algorithms suitable for edge and mobile environments. Particular attention should be given to optimization-based fingerprint–FKP multimodal recognition, where advanced algorithms such as WOA and GWO offer significant potential for improving recognition accuracy, computational efficiency, and system robustness.

Overall, optimization algorithms remain fundamental to the advancement of modern biometric recognition systems. Their continued development and integration with emerging artificial intelligence technologies will be essential for building accurate, efficient, scalable, and secure next-generation authentication systems.

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