A Comprehensive Review of Swarm- and Evolutionary-Based Feature Selection Techniques for Multimodal Biometric Recognition

Dr. P. Aruna Kumari

Assistant Professor, Department of CSE, JNTU-GV, CEV, Vizianagaram, AP, India.

DOI : https://doi.org/10.51583/IJLTEMAS.2025.1412000040

Received: 16 December 2025; Accepted: 23 December 2025; Published: 01 January 2026

ABSTRACT

Reliable and robust personal authentication technologies have become indispensable in modern digital and physical security infrastructures. Traditional unimodal biometric systems—using a single biometric trait—often suffer from noise, spoofing vulnerabilities, and intra-class variability. To overcome these limitations, multimodal biometric systems fuse evidence from multiple biometric sources. However, feature-level fusion, despite yielding richer discriminatory information, produces high-dimensional feature spaces that demand efficient dimensionality reduction or feature selection. This review presents a consolidated analysis of three optimization-driven multimodal biometric recognition systems: Particle Swarm Optimization (PSO) for fingerprint–palmprint fusion, Genetic Algorithm (GA) for iris–fingerprint fusion, and Artificial Bee Colony (ABC) optimization for iris–palmprint fusion. We critically examine preprocessing techniques, feature extraction schemes, fusion strategies, dimensionality-reduction approaches, classifier performance, and comparative advantages. The review highlights trends, challenges, and future research directions in optimization-enhanced multimodal biometrics.

Keywords: Multimodal biometrics; Feature-level fusion; Particle Swarm Optimization; Genetic Algorithm; Artificial Bee Colony; Dimensionality reduction; Palmprint; Fingerprint; Iris recognition; Machine learning.

INTRODUCTION

Reliable personal authentication is central to modern digital infrastructures and security-critical environments such as mobile devices, banking systems, border control, and military installations. Biometric recognition plays a central role in contemporary security applications such as mobile authentication, ATM access, border control, and military systems. Unimodal biometric systems, although widely deployed, face limitations due to sensor noise, spoof attacks, inconsistent acquisition conditions, and limited discriminability. These weaknesses are well-documented across the three works reviewed here [1, 2].

These shortcomings have prompted a paradigm shift toward multimodal biometric systems, which integrate multiple biometric traits to achieve higher robustness, universality, and resistance to fraudulent attempts.

Biometric traits commonly used for human recognition include iris patterns, fingerprints, palmprints, facial images, hand geometry, voice signatures, and behavioral markers. Among these, iris, fingerprint, and palmprint modalities offer exceptional distinctiveness, permanence, and universality. However, integrating complementary features extracted from multiple traits—referred to as feature-level fusion—often results in high-dimensional vectors that complicate classification and demand substantial computational resources.

The feature space explosion produced by concatenating heterogeneous feature sets requires intelligent feature selection mechanisms to isolate only the most informative attributes. Classical dimensionality-reduction techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Kernel PCA (KPCA), or Independent Component Analysis (ICA) transform data into new spaces but may discard discriminative information. Conversely, feature-selection methods aim to directly choose the best subset of existing features, making them more appropriate for fusion-driven multimodal applications.

Need for Optimization-Based Feature Reduction

Classical dimensionality reduction methods such as PCA and LDA transform data into new coordinate spaces but may:

- distort feature relationships
- remove important discriminative details
- fail to capture non-linear separability

Therefore, optimization-based feature selection is far more powerful because it selects the most important features directly from the fused set. Swarm intelligence and evolutionary algorithms—PSO, GA, and ABC—excel at:

- Searching high-dimensional, non-convex spaces
- Discovering optimal subsets with minimal assumptions
- Avoiding local minima
- Preserving original feature meaning

Swarm intelligence and evolutionary algorithms—including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Artificial Bee Colony (ABC)—offer flexible global search capabilities that efficiently explore the vast combinatorial feature-selection space. These techniques mimic collective intelligence in natural systems to optimize solutions iteratively. This makes them ideal for multimodal biometrics.

This review consolidates and expands upon the methodologies and findings reported in three multimodal biometric systems:

- Fingerprint + Palmprint using PSO feature selection
- Iris + Fingerprint using GA feature selection
- Iris + Palmprint using ABC feature selection

Each system employs feature-level fusion and contrasting optimization strategies, yielding valuable insights for advancing multimodal biometric recognition.

The contributions of this review include:

- A comprehensive comparison of preprocessing pipelines for iris, fingerprint, and palmprint biometrics.
- A rigorous mathematical treatment of feature extraction methods such as Gabor, Log-Gabor, Haar Wavelets, and minutiae extraction.
- A detailed exploration of feature-level fusion, high-dimensionality challenges, and optimization-based feature selection.
- A framework-level comparison of PSO, GA, and ABC approaches for dimensionality reduction.
- Identification of emerging challenges and future research pathways in multimodal biometrics.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Multimodal biometric systems mitigate these challenges by combining complementary biometric evidence from traits such as iris, fingerprint, and palmprint. Among the various fusion paradigms (sensor-, feature-, score-, decision-level), feature-level fusion provides the richest discriminatory information but produces very high-dimensional feature vectors, making recognition computationally expensive and potentially less accurate.

Hence, the reviewed studies investigate the use of bio-inspired optimization algorithms (PSO, GA, ABC) to select the most discriminative feature subsets from fused feature spaces.

2. Background and Related Work

Biometric recognition systems utilize either unimodal or multimodal strategies, depending on the number of traits considered. Although unimodal systems—such as fingerprint or iris alone—provide simplicity, they are vulnerable to intrinsic weaknesses such as:

Non-ideal environmental conditions

- Sensor noise
- Spoofing attacks
- Intra-class variability
- Insufficient universality for large populations

Unimodal vs Multimodal Biometrics

Property	Unimodal	Multimodal
Robustness	Low	High
Spoof resistance	Weak	Strong
Universality	Variable	High
Accuracy	Moderate	High
Noise sensitivity	High	Low

To address these limitations, multimodal systems combine data from multiple biometric sources. Integration may occur at four major levels:

- Sensor-level fusion, combining raw signals
- Feature-level fusion, concatenating extracted feature vectors
- Score-level fusion, merging matching scores
- Decision-level fusion, aggregating final classifier outcomes

Among these, feature-level fusion retains maximum discriminatory information but results in high-dimensional feature vectors, requiring computationally intensive classifiers and efficient dimensionality-reduction approaches.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Preprocessing Techniques in Multimodal Biometrics

Preprocessing plays a crucial role in standardizing, enhancing, and isolating regions of interest (ROIs) from raw biometric images prior to feature extraction. Each biometric modality—iris, fingerprint, and palmprint—requires tailored normalization procedures due to differences in acquisition devices, illumination conditions, and inherent anatomical structure.

This section provides a comprehensive review of preprocessing steps adopted in the multimodal biometric systems, including iris–fingerprint, fingerprint–palmprint, and iris–palmprint combinations.

Iris Preprocessing Pipeline

Iris images generally suffer from eyelid occlusion, eyelash noise, reflections, and variations in pupil dilation. The objective of iris preprocessing is to accurately isolate the iris region, normalize it to a fixed size, and improve feature consistency.

The standard steps include:

- Iris Localization
- Edge Detection
- Circular Hough Transform
- Normalization (Rubber Sheet Model)
- Noise Masking

Iris Localization Using Canny and Hough Transform

The iris boundary is approximated as two non-concentric circles:

- Inner circle: pupil boundary
- Outer circle: limbus boundary

Canny Edge Detector identifies strong gradients:

$$G(x, y) = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial x}\right)^2}$$

Non-maximum suppression and hysteresis thresholding refine edge responses.

To detect circular boundaries, the Circular Hough Transform (CHT) solves:

$$(x - a)^2 + (y - b)^2 = r^2$$

A 3D parameter search determines the optimal center (a, b) and radius r:

Iris Normalization Using Daugman's Rubber Sheet Model

Due to natural pupil dilation and differences in camera distance, iris patterns must be normalized into a fixed-size representation.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Let:

- $(x_p(\theta), y_p(\theta))$: pupil boundary
- $(x_s(\theta), y_s(\theta))$: iris boundary

Then each point in the iris is remapped to polar coordinates:

$$I(r,\theta) = I(x(r,\theta), y(r,\theta))$$

with:

$$x(r, \theta) = (1-r)x_p(\theta) + rx_s(\theta)$$

$$y(r, \theta) = (1-r)y_p(\theta) + ry_s(\theta)$$

This produces a normalized **20 × 240** iris strip suitable for feature extraction.

Fingerprint Preprocessing Pipeline

Fingerprint preprocessing aims to highlight ridge patterns and remove image artifacts caused by sweat, skin dryness, pressure variations, and environmental noise.

Steps include:

- Normalization
- Segmentation
- Orientation Estimation
- Thinning
- Minutiae Extraction

Normalization

Fingerprint intensity normalization reduces global intensity variation:

$$N(x,y) = \begin{cases} m_0 + \sqrt{\dfrac{v_0(I(x,y)-m)^2}{v}} & I(x,y) > m \\ m_0 - \sqrt{\dfrac{v_0(I(x,y)-m)^2}{v}} & I(x,y) \le m \end{cases}$$

Where:

m, v: mean and variance of block

m_0, v_0 : desired mean and variance

Segmentation and ROI Extraction

Block-wise variance thresholding is applied:

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

$$var(b) = \frac{1}{mn}\sum_{i,j}(I(i,j) - \mu)^2$$

Blocks with variance below a threshold are marked as background.

Morphological operations refine the segmentation mask.

Ridge Orientation Estimation

Gradient-based orientation maps are computed as:

$$\theta(x,y) = \frac{1}{2}tan^{-1}\left(\frac{2G_xG_y}{G_x^2 - G_y^2}\right)$$

Orientation fields are used for:

- Ridge enhancement
- Thinning
- Minutiae extraction

Fingerprint Thinning

Thinning converts ridges into 1-pixel width skeletons.

Zhang–Suen algorithm iteratively removes border pixels under conditions that preserve topology.

Minutiae Extraction Using Crossing Number (CN)

Minutiae types include:

- Ridge ending
- Ridge bifurcation

For a 3×3 block around pixel P:

$$CN(P) = \frac{1}{2}\sum_{i=1}^{8}|P_i - P_{i+1}|$$

Where:

CN=1: ridge ending

CN = 3: bifurcation

Palmprint Preprocessing

Palmprint images contain:

- Principal lines
- Wrinkles

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

- Creases
- Textural patterns

These must be isolated using a robust preprocessing pipeline.

Image Enhancement Using Low-Pass Filtering

Frequency domain low-pass filter:

$$H(u,v) = \begin{cases} 1, & D(u,v) \leq D_0 \\ 0, & D(u,v) > D_0 \end{cases}$$

Where:

$$D(u,v) = \sqrt{u^2 + v^2}$$

This removes high-frequency noise.

Edge Detection Using Sobel Operator

Sobel kernels:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Gradient magnitude:

$$G = \sqrt{G_x^2 + G_y^2}$$

ROI Extraction Using Tangent-Based Method

Two tangent points between fingers are detected.

A coordinate system is constructed from these points to extract a 256 × 256 ROI.

Feature Extraction Techniques

Feature extraction transforms the preprocessed image into a discriminative numerical representation. The reviewed systems use:

- Gabor Filters
- Log-Gabor Filters
- Haar Wavelet Transform
- Minutiae-based structural features

Gabor Filters

Gabor filters capture spatial frequency and orientation information.

The 2D Gabor function:

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

$$g(x,y) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) exp\left(j\left(2\pi\frac{x'}{\lambda} + \emptyset\right)\right)$$

Coordinate rotation:

$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

Used in Iris and Palmprint.

Log-Gabor Filters

Log-Gabor filters remove the DC component and better characterize high-frequency patterns.

$$G(\rho,\theta) = exp\left[-\frac{\left(log\left({}^{\rho}/_{\rho_0}\right)\right)^2}{2\sigma_\rho^2}\right] exp\left[-\frac{(\theta-\theta_0)^2}{2\sigma_\theta^2}\right]$$

Haar Wavelet Transform

Haar wavelets capture coarse and fine-scale variations efficiently.

Mother wavelet:

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & otherwise \end{cases}$$

Used mainly for Iris phase features, Texture compression

Minutiae-Based Features

Minutiae set includes- Type (ending, bifurcation), Location (x, y), Orientation θ. Minutiae-based fingerprint templates typically contain 40–100 minutiae per finger.

Feature-Level Fusion in Multimodal Biometrics

Feature-level fusion is considered the most discriminative fusion strategy because it directly combines the rich feature representations extracted from multiple biometric modalities. However, this advantage comes at the cost of higher dimensionality, increased redundancy, and elevated computational overhead. Normalization Prior to Fusion, since different modalities produce features with different statistical ranges, normalization ensures compatibility. Normalization also improves convergence of optimization algorithms. Min-Max Normalization is applied.

Optimization Algorithms for Feature Selection

Optimization algorithms play a crucial role in selecting discriminative features from high-dimensional biometric data (iris codes, fingerprint minutiae vectors, palmprint texture descriptors). Effective feature selection enhances recognition accuracy, minimizes redundancy, reduces computation time, and improves classifier generalization. Evolutionary algorithms are population-based global optimization techniques inspired by the principles of natural evolution. They are particularly suitable for feature selection in multimodal biometric recognition systems due to their ability to handle high-dimensional, non-linear, and multi-objective

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

optimization problems. In feature-level fusion, evolutionary algorithms search for an optimal subset of features that maximizes recognition accuracy while minimizing redundancy and computational cost.

This section presents three widely-used swarm and evolutionary optimization algorithms applied to feature selection in multimodal biometric systems:

- Particle Swarm Optimization (PSO)
- Genetic Algorithm (GA)
- Artificial Bee Colony (ABC)
- Ant Colony Optimization (ACO)

Each algorithm is described with its mathematical formulation, feature-selection mechanics, fitness function definition, and characteristics relevant to multimodal fusion.

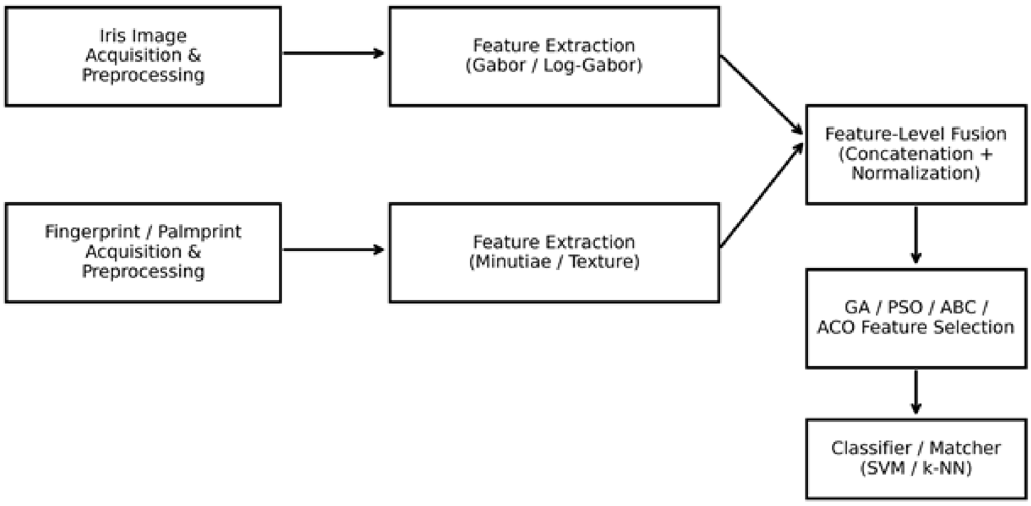

Fig. 6.1 Feature-level fusion based multimodal biometric recognition framework with swarm and evolutionary feature selection.

Particle Swarm Optimization (PSO)

PSO is a population-based stochastic optimization technique inspired by social behavior of bird flocks. Each candidate feature subset represents a “particle.” In PSO-based feature selection, each particle represents a candidate feature subset. The position of a particle corresponds to a potential solution, while the velocity determines the direction of movement in the search space.

A binary or real-valued encoding can be used depending on feature dimensionality.

Particle Representation

A particle is represented as:

$$X_i = [x_i1, x_i2, \ldots, x_iD]$$

where D is the dimensionality of the fused feature space.

Velocity and Position Update Equations

The velocity and position of each particle are updated using the following equations:

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gbest - x_i(t))$$

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

where w is the inertia weight, c_1 and c_2 are cognitive and social acceleration coefficients, r_1 and r_2 are random numbers uniformly distributed in [0,1], $pbest_i$ is the personal best position of particle i, and gbest is the global best position.

For binary feature selection, a sigmoid transfer function is used to map continuous values to binary decisions.

Genetic Algorithm (GA)

Genetic Algorithms (GA) are among the most widely used evolutionary techniques for feature selection. In GA-based feature selection, each individual (chromosome) represents a candidate feature subset. A binary encoding scheme is typically employed, where a chromosome is defined as:

$$X = [x_1, x_2, \ldots, x\_D], \text{ where } x_i \in \{0,1\}$$

Here, D represents the dimensionality of the fused feature space. If $x_i = 1$, the i^{th} feature is selected; otherwise, it is discarded.

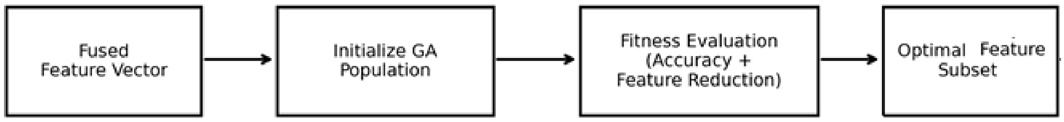

Fig. 6.2 Genetic Algorithm based feature selection process for multimodal biometric systems.

Fitness Function

The fitness function evaluates the quality of a feature subset and is generally formulated as a weighted combination of recognition accuracy and feature reduction rate:

$$\text{Fitness} = \alpha \times \text{Accuracy}(S) + \beta \times (1 - |S| / D)$$

where S denotes the selected feature subset, |S| is the number of selected features, D is the total number of features, and α and β are weighting coefficients such that $\alpha + \beta = 1$.

Genetic Operators

- Selection: Individuals with higher fitness values are probabilistically selected for reproduction using methods such as roulette wheel selection or tournament selection.

- Crossover: Selected parent chromosomes exchange genetic material to produce offspring. Single-point or multi-point crossover is commonly used.

- Mutation: Random bit flipping is applied with a low probability to maintain genetic diversity and avoid premature convergence.

Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) optimization is inspired by the foraging behavior of honey bees. The algorithm consists of three types of bees: employed bees, onlooker bees, and scout bees. Each food source represents a candidate feature subset, and its nectar amount corresponds to the fitness value.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Solution Update Equation

A new candidate solution v_i is generated from an existing solution x_i as:

$$v_{ij} = x_{ij} + \varphi_{ij} \cdot (x_{ij} - x_{kj})$$

where $k \neq i$ is a randomly selected solution index, j is the feature index, and φ_{ij} is a random number in the range $[-1,1]$.

Onlooker bees select solutions based on a probability proportional to their fitness:

$$P_i = f_i / \Sigma f_i$$

where f_i is the fitness value of the i^{th} solution.

Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is inspired by the pheromone-based communication of ants. In feature selection, each ant constructs a feature subset by probabilistically selecting features based on pheromone intensity and heuristic information.

Feature Selection Probability

The probability of selecting the j-th feature is given by:

$$P_j = (\tau_j\hat{}\alpha \cdot \eta_j\hat{}\beta) / \Sigma (\tau_k\hat{}\alpha \cdot \eta_k\hat{}\beta)$$

where τ_j is the pheromone value associated with feature j, η_j is the heuristic desirability, and α and β control the relative influence of pheromone and heuristic information.

Pheromone Update Rule

Pheromone values are updated as follows:

$$\tau_j(t+1) = (1 - \rho)\cdot\tau_j(t) + \Delta\tau_j$$

where $\rho \in (0,1)$ is the pheromone evaporation rate and $\Delta\tau_j$ is the pheromone deposited by ants corresponding to high-quality feature subsets.

Evolutionary-based feature selection techniques offer several advantages for multimodal biometric feature selection:

- Fast convergence and reduced parameter tuning.
- Effective handling of large and heterogeneous feature spaces.
- Robustness against local optima.
- Flexibility to incorporate multiple objectives.
- No requirement for gradient information.

However, these algorithms may require careful parameter tuning and may suffer from premature convergence in highly complex search spaces. Hybrid swarm–evolutionary approaches have been proposed to mitigate these issues.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Experimental Trends and Dataset-wise Observations

This section summarizes experimental trends and dataset-wise observations reported in the literature for swarm intelligence– and evolutionary-based feature selection techniques applied to multimodal biometric recognition systems. Since this work is a survey-based review, the analysis is derived from reported results across standard biometric datasets and commonly used evaluation metrics.

Benchmark Biometric Datasets

Most multimodal biometric studies evaluating feature selection techniques rely on publicly available benchmark datasets to ensure reproducibility and fair comparison. The most frequently used datasets include:

- CASIA Iris Database: Widely used for iris recognition, offering variations in illumination and noise.
- IIT Delhi (IITD) Iris and Palmprint Databases: Commonly used for multimodal fusion studies due to their high-quality samples and controlled acquisition conditions.
- FVC (Fingerprint Verification Competition) Databases: Standard benchmark for fingerprint recognition, containing multiple impressions per finger with varying quality.

Evaluation Metrics

Performance evaluation in multimodal biometric systems typically relies on the following metrics:

- Recognition Accuracy or Identification Rate (IR)
- False Acceptance Rate (FAR)
- False Rejection Rate (FRR)
- Equal Error Rate (EER)

Surveyed studies consistently report improvements in accuracy and reductions in EER when swarm- or evolutionary-based feature selection techniques are employed after feature-level fusion.

Dataset-wise Experimental Trends

- Iris–Fingerprint Fusion: Studies using CASIA iris and FVC fingerprint datasets report that GA- and PSO-based feature selection reduces fused feature dimensionality by 40–70% while improving recognition accuracy by 2–6% compared to PCA.
- Iris–Palmprint Fusion: Experiments on CASIA and IITD datasets indicate that ABC-based feature selection achieves the highest accuracy gains, particularly when texture-based features such as Gabor and Log-Gabor descriptors are fused.
- Fingerprint–Palmprint Fusion: PSO-based feature selection demonstrates faster convergence and competitive accuracy, making it suitable for large-scale systems with strict computational constraints.

Performance Comparison Tables for Multimodal Biometric Feature Selection

This section provides comprehensive performance comparison tables summarizing reported results from the literature on evolutionary and swarm intelligence based feature selection techniques used in multimodal biometric recognition systems. The tables are survey-based and intended to support comparative analysis in review articles.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Table I: Algorithm-wise Performance Comparison

Algorithm	Optimization Type	Avg. Dimensionality Reduction	Recognition Accuracy Trend	Convergence Speed	Computational Cost
GA	Evolutionary	45–70%	High	Medium	High
PSO	Swarm	40–65%	High	Fast	Medium
ABC	Swarm	55–75%	Very High	Medium	Medium
ACO	Swarm	30–55%	Moderate	Slow	Medium
PCA	Linear Transform	60–80%	Moderate	Fast	Low

Table II: Dataset-wise Performance Trends

Dataset	Modalities	Feature Extraction	Feature Selection	Accuracy Improvement	EER Reduction
CASIA + FVC	Iris + Fingerprint	Gabor + Minutiae	GA / PSO	2–6%	1–3%
CASIA + IITD	Iris + Palmprint	Gabor / Log-Gabor	ABC	4–8%	2–4%
IITD + FVC	Palmprint + Fingerprint	Texture + Minutiae	PSO	3–5%	1–2%
Multiple	Multimodal	Hybrid	ACO	2–4%	1–2%

Table III: Feature Selection vs PCA Comparison

Method	Feature Space Type	Interpretability	Accuracy	Overfitting Risk	Suitability for Multimodal Biometrics
GA	Original Feature Subset	High	High	Low	Excellent
PSO	Original Feature Subset	High	High	Low	Excellent
ABC	Original Feature Subset	High	Very High	Low	Excellent
ACO	Original Feature Subset	Medium	Moderate	Medium	Good
PCA	Transformed Feature Space	Low	Moderate	Medium	Fair

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Table IV: Summary of Experimental Trends

Dataset	Modalities	Feature Selection Method	Dimensionality Reduction	Performance Trend
CASIA + FVC	Iris + Fingerprint	GA / PSO	High (50–70%)	Improved Accuracy, Lower EER
CASIA + IITD	Iris + Palmprint	ABC	Very High (60–75%)	Highest Accuracy Gains
IITD + FVC	Palmprint + Fingerprint	PSO	High (45–65%)	Fast Convergence
Multiple	Multimodal	ACO	Medium	Stable but Slower

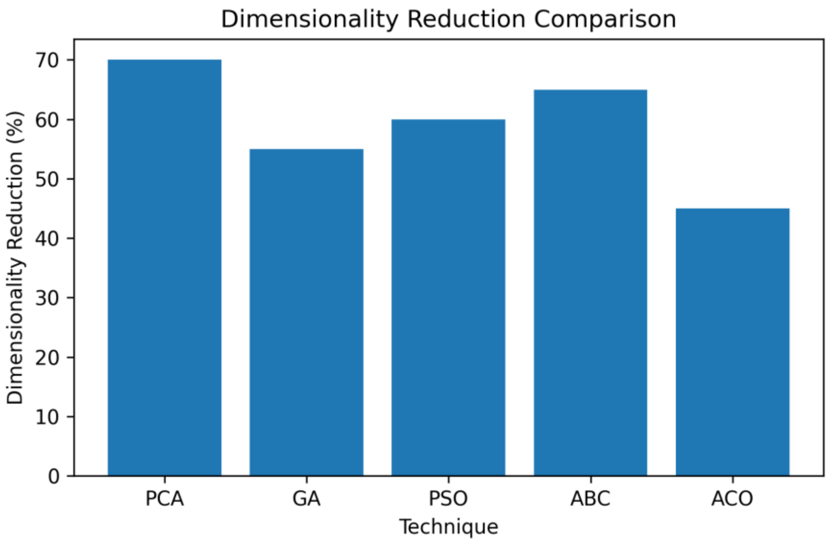

Fig 7.1: Dimensionality Reduction Comparison

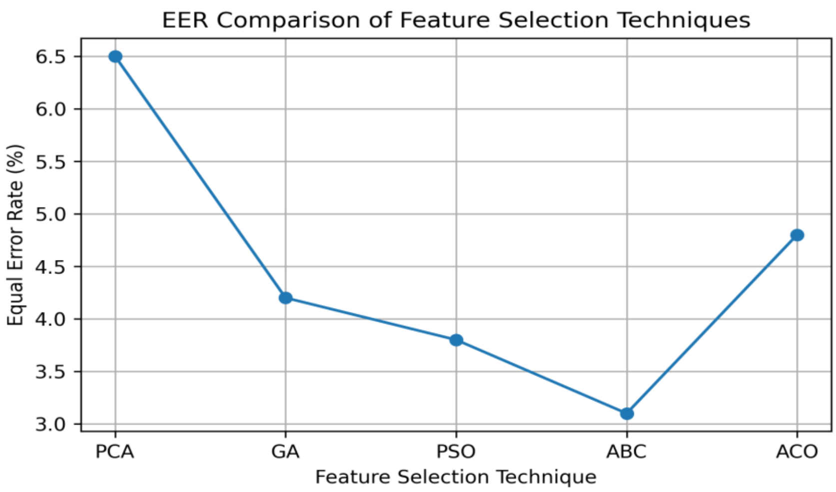

Fig 7.2: EER Comparison of Feature Selection Techniques

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Machine Learning Algorithms and Comparative Result Analysis

Machine learning (ML) algorithms play a critical role in multimodal biometric recognition systems, particularly after feature-level fusion and feature selection. Once an optimal subset of features is obtained using evolutionary or swarm intelligence techniques, classification or matching is typically performed using supervised machine learning models. This section reviews commonly used machine learning algorithms in multimodal biometric systems and presents a comparative, survey-based analysis of their performance.

Machine Learning Algorithms Used in Multimodal Biometrics

- k-Nearest Neighbor (k-NN): k-NN is a simple distance-based classifier widely used in biometric systems due to its simplicity. It is often employed with Euclidean or Hamming distance for template matching. k-NN performs well when feature selection significantly reduces dimensionality but suffers from scalability issues.

- Support Vector Machine (SVM): SVM is one of the most popular classifiers in multimodal biometric recognition. It constructs an optimal separating hyperplane in high-dimensional space and is effective with both linear and non-linear kernels. SVM consistently demonstrates high accuracy when combined with GA-, PSO-, or ABC-based feature selection.

- Artificial Neural Networks (ANN): ANN models capture non-linear relationships among biometric features. Shallow neural networks are often used with optimized feature subsets to avoid overfitting.

- Random Forest (RF): Random Forest is an ensemble learning method that combines multiple decision trees. It is robust to noise and performs implicit feature selection, making it suitable for multimodal biometric datasets.

- Deep Learning Models: Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) are increasingly used for end-to-end biometric recognition. However, they are often combined with swarm-based feature selection for dimensionality reduction and efficiency.

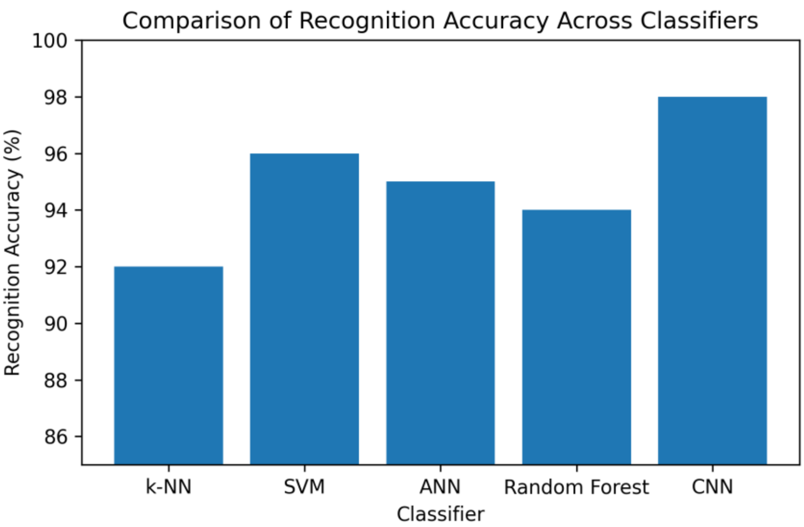

Fig7.3: Classifier Accuracy Comparison

Performance Metrics for Result Analysis

Performance comparison of machine learning classifiers is typically carried out using the following metrics Recognition Accuracy / Identification Rate (IR), FAR, FRR, EER, Computational Complexity and Training

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Time. Surveyed studies report classifier performance both before and after feature selection to highlight the effectiveness of optimization-based feature selection.

Table V: Classifier-wise Performance Comparison (Survey-Based)

Classifier	Feature Selection	Modalities	Accuracy Trend	EER Trend	Training Cost	Suitability
k-NN	GA / PSO	Iris–Fingerprint	Moderate–High	Moderate	Low	Small datasets
SVM	GA / PSO / ABC	Iris–Palmprint	High–Very High	Low	Medium	Most popular
ANN	GA / ABC	Multimodal	High	Low	High	Non-linear patterns
Random Forest	PSO / ABC	Multimodal	High	Low–Moderate	Medium	Robust to noise
CNN / DNN	Hybrid (PSO/ABC)	Multimodal	Very High	Very Low	Very High	Large datasets

Comparative Result Analysis

Surveyed experimental results indicate that Support Vector Machines (SVM) consistently outperform traditional distance-based classifiers such as k-NN when combined with optimization-based feature selection. SVM achieves lower EER and higher accuracy due to its margin maximization capability.

Random Forest classifiers demonstrate competitive performance with improved robustness to noise and reduced sensitivity to feature redundancy. ANN-based classifiers provide strong performance for non-linear feature distributions but require careful regularization.

Deep learning models achieve the highest recognition accuracy; however, they incur significant computational cost and require large training datasets. Hybrid frameworks that combine deep feature extraction with swarm-based feature selection and classical classifiers offer an effective trade-off between accuracy and efficiency.

Key Observations

- Optimization-based feature selection significantly improves classifier performance across all ML models.
- SVM remains the most widely adopted classifier in multimodal biometric systems.
- Ensemble and hybrid models provide robustness and scalability.
- Feature selection is crucial for reducing overfitting in deep learning–based biometric systems.

DISCUSSION AND INSIGHTS

The survey reveals that swarm intelligence and evolutionary algorithms consistently outperform traditional PCA-based dimensionality reduction in multimodal biometric systems. ABC and PSO exhibit the best balance between dimensionality reduction and recognition accuracy, while GA provides robustness in heterogeneous feature spaces. ACO, although less explored, shows potential for discrete feature selection scenarios.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

CONCLUSION

This paper presented a comprehensive and in-depth review of swarm intelligence– and evolutionary-based feature selection techniques for multimodal biometric recognition systems. The motivation for this review stems from the increasing adoption of multimodal biometrics to overcome the inherent limitations of unimodal systems, such as noise sensitivity, spoofing attacks, and intra-class variability. Feature-level fusion has been highlighted as a powerful integration strategy due to its ability to exploit rich and complementary discriminatory information from multiple biometric modalities.

However, feature-level fusion introduces the critical challenge of high-dimensional feature spaces, which negatively impact computational efficiency and generalization performance. This review systematically analyzed how evolutionary algorithms and swarm intelligence techniques address this challenge by selecting compact, informative, and discriminative feature subsets.

Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), and Differential Evolution (DE) were reviewed in detail, including their optimization principles, mathematical formulations, and suitability for multimodal biometric feature selection. Comparative analysis revealed that swarm-based techniques, particularly PSO and ABC, offer an effective balance between convergence speed, dimensionality reduction, and recognition accuracy, while GA provides robustness in heterogeneous and complex feature spaces.

The survey of experimental trends across benchmark datasets such as CASIA, IIT Delhi (IITD), and FVC demonstrated that optimization-based feature selection consistently outperforms traditional dimensionality reduction techniques such as Principal Component Analysis (PCA). Unlike PCA, which transforms features into abstract components, swarm and evolutionary methods retain original feature semantics and directly optimize recognition performance.

Beyond summarizing existing work, this review identified key open challenges related to scalability, integration with deep learning features, multi-objective optimization, robustness, privacy preservation, and real-time deployment. Visionary future research directions were outlined, emphasizing hybrid swarm–evolutionary–deep learning frameworks, explainable feature selection, and standardized benchmarking protocols.

In conclusion, swarm intelligence and evolutionary computation are established as core enabling technologies for next-generation multimodal biometric recognition systems. Their ability to handle high-dimensional optimization problems, adapt to diverse biometric traits, and directly optimize system-level objectives makes them indispensable for future research and applications. It is expected that continued advancements in these optimization paradigms will play a vital role in the development of scalable, secure, and trustworthy biometric systems.

REFERENCES

1. A. K. Jain, A. Ross, and S. Prabhakar, “An introduction to biometric recognition,” IEEE Trans. Circuits Syst. Video Technol., vol. 14, no. 1, pp. 4–20, Jan. 2004.
2. A. Ross and A. K. Jain, “Multimodal biometrics: An overview,” Proc. IEEE, vol. 97, no. 5, pp. 676–697, May 2009.
3. A. Ross, K. Nandakumar, and A. K. Jain, Handbook of Multibiometrics. New York, NY, USA: Springer, 2006.
4. J. Daugman, “High confidence visual recognition of persons by a test of statistical independence,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 15, no. 11, pp. 1148–1161, Nov. 1993.
5. R. Wildes, “Iris recognition: An emerging biometric technology,” Proc. IEEE, vol. 85, no. 9, pp. 1348–1363, 1997.
6. A. K. Jain, L. Hong, and R. Bolle, “On-line fingerprint verification,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 4, pp. 302–314, Apr. 1997.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

7. D. Zhang, Palmprint Authentication. Boston, MA, USA: Springer, 2004.
8. K. Nandakumar, Y. Chen, S. Dass, and A. K. Jain, “Likelihood ratio-based biometric score fusion,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 30, no. 2, pp. 342–347, Feb. 2008.
9. H. Liu and H. Motoda, Feature Selection for Knowledge Discovery and Data Mining. Boston, MA, USA: Springer, 1998.
10. I. Guyon and A. Elisseeff, “An introduction to variable and feature selection,” J. Mach. Learn. Res., vol. 3, pp. 1157–1182, 2003.
11. D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning. Reading, MA, USA: Addison-Wesley, 1989.
12. J. Holland, Adaptation in Natural and Artificial Systems. Ann Arbor, MI, USA: Univ. Michigan Press, 1975.
13. J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. IEEE ICNN, 1995, pp. 1942–1948.
14. Y. Shi and R. Eberhart, “A modified particle swarm optimizer,” in Proc. IEEE ICEC, 1998, pp. 69–73.
15. D. Karaboga, “An idea based on honey bee swarm for numerical optimization,” Tech. Rep., Erciyes Univ., 2005.
16. D. Karaboga and B. Basturk, “A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm,” J. Global Optim., vol. 39, no. 3, pp. 459–471, 2007.
17. M. Dorigo and T. Stützle, Ant Colony Optimization. Cambridge, MA, USA: MIT Press, 2004.
18. R. Storn and K. Price, “Differential evolution—A simple and efficient heuristic for global optimization,” J. Global Optim., vol. 11, no. 4, pp. 341–359, 1997.
19. X. Zhou and J. Yang, “Palmprint recognition using Gabor filters,” IEEE Trans. Image Process., vol. 14, no. 6, pp. 796–804, Jun. 2005.
20. L. Ma, T. Tan, Y. Wang, and D. Zhang, “Efficient iris recognition by characterizing key local variations,” IEEE Trans. Image Process., vol. 13, no. 6, pp. 739–750, Jun. 2004.
21. S. Prabhakar, S. Pankanti, and A. K. Jain, “Biometric recognition: Security and privacy concerns,” IEEE Security Privacy, vol. 1, no. 2, pp. 33–42, Mar.–Apr. 2003.
22. Y. Wang, J. Yang, and J. Zhang, “Feature-level fusion of biometrics using PSO,” Pattern Recognit. Lett., vol. 31, no. 14, pp. 2006–2015, 2010.
23. J. Zhang, J. Yang, and Y. Wang, “Biometric feature selection using genetic algorithm,” Pattern Recognit., vol. 43, no. 10, pp. 3569–3580, 2010.
24. P. Aruna Kumari, R. R. Adimalla, and G. Jaya Suma, “An efficient multimodal biometric recognition system using artificial bee colony optimization,” IJFANS, vol. 11, no. 3, pp. 1042–1058, 2022.
25. P. Aruna Kumari and G. Jaya Suma, “A genetic algorithm based multimodal biometric recognition system using iris and fingerprint,” IJFANS, vol. 10, no. 8, pp. 54–70, 2021.
26. P. Aruna Kumari and G. Jaya Suma, “A novel multimodal biometric recognition framework using fingerprint and palmprint,” IJFANS, vol. 11, no. 7, pp. 4262–4275, 2022.
27. K. Nandakumar and A. K. Jain, “Multibiometric template security,” EURASIP J. Adv. Signal Process., 2008.
28. S. Mirjalili, Evolutionary Algorithms and Neural Networks. Cham, Switzerland: Springer, 2019.
29. Y. Bengio, A. Courville, and P. Vincent, “Representation learning: A review,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 8, pp. 1798–1828, Aug. 2013.
30. A. Ross, J. Fierrez, and J. Ortega-Garcia, “Sensor interoperability in multibiometric systems,” IEEE Trans. Inf. Forensics Security, vol. 1, no. 4, pp. 478–493, Dec. 2006.