Multi-Algorithm Biometric Person Authentication Using Artificial Bee Colony Based Feature Selection

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***Abstract*—Multimodal biometric systems enhance person authentication by combining complementary information from multiple traits to overcome the limitations of unimodal systems such as noisy data, spoof attacks, intra-class variations, and non-universality [1][2]. In this work, a multi-algorithm feature-level fusion framework is proposed using fingerprint, iris, and palmprint modalities, where multiple feature extractors per trait are integrated into a common high-dimensional feature space [3][4]. To address the dimensionality problem and improve recognition accuracy, a basic Artificial Bee Colony (ABC) algorithm is employed as a wrapper-based feature selection method driven by a classification-based fitness function [5]. The binary ABC mechanism, employing employed bees, onlooker bees, and scout bees' phases, effectively identifies the most discriminative feature subsets while reducing computational complexity [6]. Experimental evaluation on publicly available CASIA, IITD, and FVC benchmark databases demonstrates that the proposed ABC-based multi-algorithm system attains high recognition accuracy (96.5% 97.5% with Euclidean distance, 99% 99.4% with supervised classifiers) with significantly reduced feature dimension (80% 89% reduction) compared with PCA-only feature reduction and non-optimized baselines [7]. The results confirm that ABC-driven selection of discriminative features at the fusion layer offers an effective balance between accuracy, feature compactness, and computational efficiency in real-time biometric person authentication.**

***Index Terms*—Multimodal biometrics; multi-algorithm fusion; feature-level fusion; artificial bee colony; feature selection; wrapper method; fingerprint; iris; palmprint; person authentication; biometric recognition; swarm intelligence; optimization.**

I. INTRODUCTION

1.1 Background and Motivation

Reliable person authentication is a critical requirement in a wide range of application domains, including electronic commerce, automated banking, law enforcement, border control, and smart device security [1]. Biometric authentication systems address this need by leveraging distinctive physiological or behavioral characteristics such as fingerprints, irises, and palmprints to establish or verify individual identity [2]. Although unimodal biometric systems, which rely on a single biometric trait, offer advantages in terms of simplicity and deployment cost, they are inherently constrained by several fundamental limitations [3].

In practice, unimodal systems are susceptible to noisy data arising from imperfect sensors, suboptimal acquisition conditions, and environmental influences [4]. Intra class variations further degrade recognition performance, as biometric samples from the same individual may differ due to rotation, translation, pressure variation, postural changes, sensor interoperability issues, or aging effects [4]. Non universality poses an additional challenge, as certain users may be unable to provide reliable instances of specific biometric traits because of physical disabilities, injuries, or medical conditions [4]. Moreover, unimodal systems are more vulnerable to spoofing attacks, wherein adversaries attempt to forge or replicate a single biometric characteristic particularly in the case of behavioral modalities [4]. Finally, limited distinctiveness in some biometric traits can lead to overlapping feature representations across individuals, thereby reducing discriminative capability and increasing false matches [4].

To overcome these limitations, multimodal biometric systems integrate complementary information from multiple biometric sources, including multiple traits (multimodal), multiple samples or instances, and multiple feature extraction algorithms per trait (multi-algorithm) [2][5]. Among various fusion strategies, feature-level fusion combines feature representations at an early stage of the recognition pipeline, preserving rich discriminatory information and often yielding superior authentication performance compared to score-level or decision-level fusion approaches [3]. However, direct concatenation of heterogeneous feature vectors produces highly high-dimensional fused feature spaces, which exacerbate the curse of dimensionality. This results in increased computational complexity, higher memory requirements, potential degradation in recognition accuracy, and reduced suitability for real-time authentication in large-scale biometric systems [3][4].

1.2 The Dimensionality Reduction Problem

Feature-level fusion in multimodal biometric systems often results in high-dimensional feature spaces, which pose several critical challenges to system efficiency and performance [3][4]. First, computational complexity increases significantly with large feature vectors, leading to longer training and testing times and limiting the feasibility of real-time authentication in large-scale deployments [4]. Second, memory and storage requirements grow substantially, increasing both storage costs and communication bandwidth demands [4]. Third, classification accuracy may deteriorate, as not all features contribute equally to discriminatory power; redundant or noisy features can negatively impact classifier performance, particularly under the small sample size (SSS) problem [3]. Finally, the curse of dimensionality becomes prominent when the dimensionality of the feature space is high relative to the number of available training samples, resulting in poor generalization and increased risk of overfitting in pattern recognition systems [3].

To mitigate these issues, dimensionality reduction techniques are commonly employed and can be broadly categorized into two approaches [4]. Feature extraction methods transform the original feature space into a lower-dimensional representation, such as Principal Component Analysis (PCA). Although effective in reducing dimensionality, these methods often sacrifice the physical interpretability of features and do not reduce feature acquisition or measurement costs [4]. In contrast, feature selection techniques identify and retain only the most informative subset of the original features, thereby preserving their physical meaning while simultaneously reducing computational and acquisition overhead [4].

In this work, we adopt a feature selection strategy based on the basic Artificial Bee Colony (ABC) algorithm to optimize feature subsets at the feature-level fusion stage in multi-algorithm, multimodal biometric systems.

1.3 Contributions and Scope

The principal contributions of this work are summarized as follows:

1. We propose a feature-level multi-algorithm, multimodal biometric framework that integrates fingerprint, iris, and palmprint modalities, employing multiple feature extraction algorithms per trait to enhance complementary discriminatory information [7].
2. We introduce a binary Artificial Bee Colony (ABC)-based wrapper feature selection approach, tailored for discrete feature subset optimization via binary encoding and sigmoid-based thresholding, enabling effective exploration of high-dimensional fused feature spaces [6].
3. We conduct extensive experimental validation on widely used benchmark datasets (CASIA, IITD, and FVC), comparing the proposed ABC-based feature selection method with Principal Component Analysis (PCA) and a no-selection baseline using both distance-based matching (Euclidean distance) and supervised classifiers (C4.5, SMO, and Naive Bayes) [7].
4. Experimental results demonstrate substantial dimensionality reduction (80% 89%) while achieving consistently high recognition rates (99% 99.4%), particularly with supervised classifiers in multi-algorithm and multimodal configurations, confirming the effectiveness and scalability of the proposed approach.

1.4 Organization

The remainder of this paper is organized as follows. Section 2 reviews related work on unimodal and multimodal biometric systems, feature-level fusion strategies, and feature selection techniques. Section 3 presents the proposed system architecture, including preprocessing, multi-algorithm feature extraction, and feature-level fusion for fingerprint, iris, and palmprint modalities. Section 4 details the proposed methodology, describing the basic Artificial Bee Colony (ABC) algorithm, problem formulation, binary feature encoding, fitness function, and the employed, onlooker, and scout bee phases. Section 5 outlines the experimental setup, benchmark databases, baseline methods, and evaluation metrics. Section 6 discusses comprehensive experimental results and performance analysis for multi-algorithmic and multimodal configurations. Finally, Section 7 concludes the paper and outlines directions for future research.

II. LITERATURE REVIEW

2.1 Unimodal Biometric Systems

2.1.1 Fingerprint Recognition System

Fingerprints consist of distinctive ridge and valley patterns formed on the fingertips, which are highly individual-specific even among identical twins and remain largely invariant over an individual's lifetime [4][8]. Owing to their permanence, uniqueness, and ease of acquisition, fingerprint recognition systems are extensively deployed in civilian applications, forensic investigations, and law enforcement environments [4].

A typical fingerprint recognition system comprises three fundamental stages [4][8]. Preprocessing aims to improve fingerprint image quality and includes segmentation to isolate the fingerprint region from the background, normalization to reduce intensity variations, and enhancement techniques to strengthen ridge valley contrast. Feature extraction involves deriving discriminative representations from the processed image, which may be global features (e.g., singular points and orientation fields) or local features such as minutiae points, including ridge endings and bifurcations [4]. Among these, minutiae-based (Level-2) features are most widely adopted in automated fingerprint recognition systems due to their strong discriminative capability and robustness to common imaging variations [4]. Finally, matching is performed by comparing the extracted features with stored templates using correlation-based, minutiae-based, or ridge-based matching algorithms to establish identity or verify a claimed identity [4].

2.1.2 Iris Recognition System

The iris is the annular, pigmented structure surrounding the pupil and is characterized by highly distinctive texture patterns such as furrows, crypts, and pigment variations. These patterns are formed through random developmental processes during early life and remain remarkably stable over time [4][8]. Owing to its high degree of uniqueness even among identical twins and its strong resistance to forgery without significant risk, the iris is considered one of the most reliable biometric traits [4].

An iris recognition system typically involves three key stages [4][8]. Preprocessing focuses on accurately localizing the iris region between the pupil and the limbic boundary, followed by normalization to a fixed-size, dimensionless representation using polar coordinate transformation, commonly implemented via Daugman's rubber sheet model. Image enhancement techniques are then applied to improve contrast and highlight iris texture details [4]. Feature extraction captures the rich textural information of the iris using phase-based approaches such as Gabor or Log-Gabor filters, or alternatively through statistical texture descriptors [4]. Finally, matching is performed by comparing the generated iris codes against enrolled templates using similarity measures, most commonly the Hamming distance, to determine identity or verify a claimed match [21].

2.1.3 Palmprint Recognition System

The palmprint refers to the inner surface of the human hand and encompasses a rich set of distinctive features, including principal lines, wrinkles, minutiae points, and fine-grained texture patterns. Owing to this diversity of structural and textural information, palmprints provide high discriminative capability and are well suited for reliable biometric recognition [4][9].

A typical palmprint recognition system consists of three main stages [4][9]. Preprocessing involves binarization and contour extraction to delineate the hand region, followed by key point detection using tangent-based or bisector-based methods. Based on these key points, a stable coordinate system is established, enabling consistent extraction of a Region of Interest (ROI) from the palmprint image

[4]. Feature extraction derives discriminative representations from the ROI and may include line-based features obtained through edge detection of principal creases, statistical descriptors such as Gabor filters, wavelet coefficients, and Zernike moments, appearance-based or subspace methods (e.g., PCA, ICA, and LDA), as well as texture-based descriptors including Local Binary Patterns (LBP) and Gabor-based codes [4]. Finally, matching is performed by computing similarity scores between extracted palmprint features using appropriate distance measures or supervised classifiers to determine identity or verify a claimed match [4].

2.2 Limitations of Unimodal Systems

Despite their widespread adoption and demonstrated reliability, unimodal biometric systems are subject to several inherent limitations that can adversely affect recognition performance and system robustness [3][4]. Noisy data may arise from defective sensors or unfavorable acquisition conditions, leading to degraded feature quality. Intra-class variations occur when biometric samples from the same individual differ across acquisition sessions due to factors such as pose, illumination, or physiological changes. Limited distinctiveness is observed in certain biometric modalities, where the extracted features may not sufficiently discriminate genuine users from imposters, particularly in large-scale systems. Non-universality further constrains unimodal systems, as some individuals may be unable to provide a usable instance of a specific biometric trait. Additionally, unimodal systems are inherently more vulnerable to spoofing attacks, as adversaries may exploit the reliance on a single biometric characteristic to compromise system security [3][4].

2.3 Multimodal Biometric Systems

Multimodal biometric systems address the inherent limitations of unimodal approaches by integrating complementary information from multiple biometric sources, thereby enhancing recognition accuracy, robustness, and resistance to spoofing attacks [2][3]. Information fusion in multimodal systems can be performed at several levels [3]. Sensor-level fusion combines data acquired from multiple sensors capturing the same biometric trait. Feature-level fusion integrates feature vectors extracted from different modalities or algorithms into a unified representation. Match-score-level fusion aggregates similarity scores produced by multiple matchers, while decision-level fusion combines the final accept/reject decisions from individual classifiers.

Among these fusion strategies, feature-level fusion, which is the focus of this work, performs integration prior to classification and thus preserves richer discriminatory information than score- or decision-level fusion, often resulting in superior authentication performance [3][4]. However, direct concatenation of heterogeneous feature vectors leads to very high-dimensional fused feature spaces, which in turn introduces computational and statistical challenges. Consequently, effective dimensionality reduction and feature selection mechanisms are essential to fully exploit the benefits of feature-level fusion in multimodal biometric systems [3][4].

2.4 Feature Selection Approaches

Feature selection seeks to identify an optimal subset of features that maximizes classification performance while minimizing the dimensionality of the feature space [4]. Based on the manner in which feature relevance is evaluated, feature selection techniques are broadly classified into three categories [4]. Filter methods assess feature importance independently of the learning algorithm and are typically employed for baseline analysis, particularly in extremely high-dimensional settings. Wrapper methods evaluate candidate feature subsets by using a classifier as a black box; although computationally more expensive, they generally yield superior performance by explicitly accounting for classifier-dependent feature interactions. Embedded methods perform feature selection as part of the model training process, as exemplified by decision tree-based algorithms and regularization-based approaches [4].

In biometric recognition systems, wrapper-based feature selection is often preferred because recognition accuracy provides a direct and task-relevant measure of feature subset quality, enabling more effective capture of inter-feature dependencies and classifier-specific discriminative characteristics [4].

2.5 Evolutionary Computation in Feature Selection

Evolutionary computation (EC) algorithms are population-based, nature-inspired metaheuristics that are particularly well suited for feature selection problems involving large, complex, and non-convex search spaces [4]. By iteratively evolving a population of candidate solutions, EC methods effectively balance exploration and exploitation, enabling efficient discovery of near-optimal feature subsets.

Several EC techniques have been widely applied to feature selection [4]. Genetic Algorithms (GA) simulate biological evolution through chromosome encoding, selection, crossover, and mutation operations. Particle Swarm Optimization (PSO) is inspired by social behavior in bird flocks, where particles traverse the solution space guided by their personal best and global best positions. Artificial Bee Colony (ABC) algorithms emulate honeybee foraging behavior through the cooperative actions of employed bees (local exploitation), onlooker bees (probabilistic selection of promising solutions), and scout bees (global exploration and diversification) [6]. Cuckoo Search (CS) is motivated by the brood parasitism of cuckoo birds and employs Lévy flight based random walks to enhance global search capability.

Among these methods, ABC has demonstrated competitive or superior performance in multimodal biometric feature selection tasks, owing to its simple structure, minimal parameter tuning requirements, rapid convergence, and strong robustness across diverse datasets [5][6][10]. Accordingly, this work adopts the basic ABC algorithm based on the original formulation by Karaboga and adapts it for discrete binary feature subset selection in high-dimensional feature-level fusion scenarios.

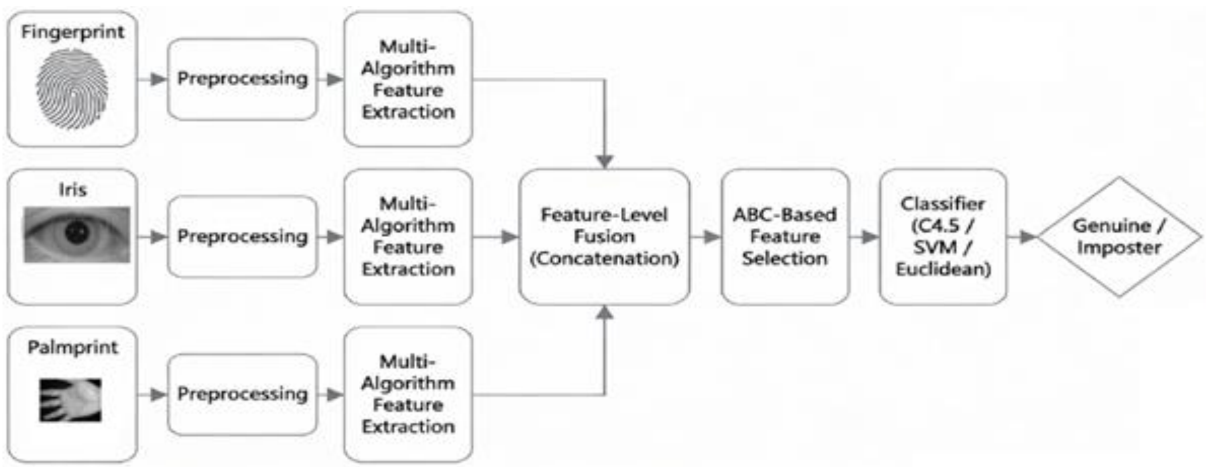

Figure 1: System Architecture

III. SYSTEM ARCHITECTURE

3.1 Overall Multi-Algorithm, Multimodal Framework

Figure 1 illustrates the proposed multi-algorithm, multimodal biometric recognition framework, which integrates fingerprint, iris, and palmprint modalities, with multiple feature extraction algorithms employed for each biometric trait [20]. Biometric images corresponding to the three modalities are acquired from standard benchmark databases, including CASIA, IITD, and FVC.

For each modality, trait-specific preprocessing is first applied, encompassing segmentation, normalization, and image enhancement to improve feature quality and robustness. Subsequently, multi-algorithm feature extraction is performed independently for each trait, where multiple complementary feature extraction algorithms (e.g., two per modality) are employed to capture diverse discriminatory characteristics. The resulting feature vectors are then combined through feature-level fusion via direct concatenation, yielding a high-dimensional fused feature vector $x \in \mathbb{R}^D$.

To address the resulting dimensionality and redundancy, an Artificial Bee Colony (ABC)-based feature selection mechanism is applied to identify an optimal binary subset mask b^*, producing a reduced feature representation x_{b^*}. Finally, the selected features are subjected to classification or matching using either distance-based measures (e.g., Euclidean distance) or supervised classifiers, resulting in a final genuine or imposter decision.

3.2 Preprocessing and Feature Extraction

3.2.1 Fingerprint Processing

Fingerprint processing begins with a sequence of preprocessing steps designed to enhance image quality and ensure reliable feature extraction [4]. Segmentation is first performed to isolate the fingerprint region from the background, typically using local ridge orientation histograms. Normalization follows to standardize pixel intensity distributions and reduce illumination variations. Enhancement techniques, such as Gabor filtering or Fourier-domain filtering, are then applied to strengthen ridge valley structures. To facilitate reliable minutiae detection, thinning is employed to reduce ridge width to a single pixel. Subsequently, minutiae extraction identifies ridge endings and bifurcations, which constitute Level-2 fingerprint features. Finally, post-processing procedures are applied to eliminate spurious minutiae using structural and statistical constraints, thereby improving feature reliability [4].

To capture complementary discriminatory information, multi-algorithm feature extraction is employed for the fingerprint modality [19]. The first approach (Algorithm F1) is a minutiae-based method that represents each fingerprint using the spatial coordinates and orientations of detected minutiae points, resulting in a feature vector $f_F^{(1)} \in \mathbb{R}^{d_F^{(1)}}$ where $d_F^{(1)} \approx 48 \quad 96$[18]. The second approach (Algorithm F2) is a texture-based method that extracts features such as Gabor-filtered energy responses or Local Binary Pattern (LBP) histograms, producing a feature vector $f_F^{(2)} \in \mathbb{R}^{d_F^{(2)}}$ where $d_F^{(2)} \approx 64 \quad 128$[18].

3.2.2 Iris Processing

Iris processing begins with a set of preprocessing operations aimed at accurate localization and enhancement of the iris texture [4][8]. Segmentation is performed to precisely identify the iris region between the pupil and the limbic boundary, typically using circular edge detection techniques. To ensure invariance to pupil dilation and image scale variations, normalization maps the segmented iris region to a fixed-size, dimensionless representation in polar coordinates, commonly implemented using Daugman's rubber sheet model [4]. Subsequently, image enhancement techniques are applied to improve contrast and highlight fine textural details within the normalized iris image [4].

To exploit complementary discriminatory information, multi-algorithm feature extraction is employed for the iris modality [16]. The first approach (Algorithm I1) is a phase-based method that utilizes Gabor or Log-Gabor filters to encode local phase information into a compact binary iris code, resulting in a feature vector $f_I^{(1)} \in \mathbb{R}^{d_I^{(1)}}$ where $d_I^{(1)} \approx 256 \quad 512$[7]. The second approach (Algorithm I2) extracts texture-based features from the normalized iris image using Local Binary Patterns (LBP) or statistical descriptors such as mean, variance, and energy, producing a feature vector $f_I^{(2)} \in \mathbb{R}^{d_I^{(2)}}$ where $d_I^{(2)} \approx 128 \quad 256$[7].

3.2.3 Palmprint Processing

Palmprint processing begins with a sequence of preprocessing steps designed to ensure accurate alignment and reliable feature extraction from the hand image [4][9]. Binarization is first applied to convert the grayscale image into a binary representation using appropriate thresholding techniques. This is followed by contour extraction to delineate the hand and palm boundaries. Key point identification is then performed to detect anatomical landmarks such as fingertips and inter-finger valleys, commonly using tangent-based approaches. Based on these landmarks, a stable coordinate system is established to achieve consistent alignment across samples. Finally, a central Region of Interest (ROI) typically square-shaped is extracted from the palm region to serve as the basis for subsequent feature extraction [4].

To capture complementary structural and textural information, multi-algorithm feature extraction is employed for the palmprint modality [17]. The first method (Algorithm P1) is a line-based approach that extracts principal lines and wrinkles using edge detection operators such as Canny or Sobel, resulting in a feature vector $f_P^{(1)} \in \mathbb{R}^{d_P^{(1)}}$ where $d_P^{(1)} \approx 64 \quad 128$[7]. The second method (Algorithm P2) is texture-based and derives features from the ROI using Gabor filter energy responses or competitive coding schemes, producing a feature vector $f_P^{(2)} \in \mathbb{R}^{d_P^{(2)}}$ where $d_P^{(2)} \approx 128 \quad 256$[15].

3.3 Feature Level Fusion

After multi-algorithm feature extraction for each trait, feature vectors are concatenated into a single fused feature vector [7]:

$$x = \left[f_F^{(1)} \parallel f_F^{(2)} \parallel f_I^{(1)} \parallel f_I^{(2)} \parallel f_P^{(1)} \parallel f_P^{(2)}\right] \in \mathbb{R}^D,$$

where $\parallel$ denotes concatenation and $D = \sum d_\cdot^{(\cdot)} \approx$ 800 2000 (depending on specific algorithm implementations and database characteristics) [14]. This high dimensionality necessitates feature selection to reduce computational complexity while preserving discriminative information.

IV. ARTIFICIAL BEE COLONY BASED FEATURE SELECTION

4.1 Problem Formulation

Feature Selection as Binary Optimization: Given a fused feature vector $x \in \mathbb{R}^D$, find a binary selection mask

$$b = [b_1, b_2, \dots, b_D], b_j \in \{0,1\},$$

such that the selected feature subvector

$$x_b = \{x_j \mid b_j = 1\}$$

maximizes a fitness function combining recognition accuracy and feature subset size [6][7].

4.2 Fitness Function

The wrapper-based fitness function evaluates each feature subset b by training a classifier on selected features and measuring recognition accuracy [4][7]:

$$\mathrm{Acc}(b) = \frac{N_{\mathrm{correct}}(b)}{N_{\mathrm{total}}},$$

Where $N_{\mathrm{correct}}(b)$ is the number of correctly classified training samples using features indicated by b, and N_{total} is the total number of training samples. Cross-validation ensures unbiased accuracy estimation [4].

To balance accuracy and feature compactness, the overall fitness is [6][7]:

$$\mathrm{Fit}(b) = \alpha \cdot \mathrm{Acc}(b) - \beta \cdot \frac{\sum_{j=1}^{D} b_j}{D},$$

Where:

- $\alpha \gg \beta > 0$ (e.g., $\alpha = 0.9, \beta = 0.1$)[6].
- The first term prioritizes recognition accuracy.
- The second term penalizes larger feature subsets to encourage compactness.

Higher $\mathrm{Fit}(b)$ indicates a better feature subset [6][7].

4.3 Basic ABC Algorithm Core (Continuous Formulation)

The original ABC algorithm (Karaboga) is formulated for continuous optimization [6]. For continuous problems, each candidate solution (food source) is represented as $x_i = [x_{i1}, x_{i2}, \dots, x_{iD}]$. The employed bee updates its food source using a neighbor-based mechanism [6]:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}),$$

Where:

- $k \neq i$ is a randomly chosen food source index [6].
- $\phi_{ij} \sim \mathcal{U}(-1,1)$ is a random number controlling neighbor exploration [6].

Onlooker bees select food sources with probability [6]:

$$p_i = \frac{\mathrm{Fit}_i}{\sum_{m=1}^{SN} \mathrm{Fit}_m},$$

Where SN is the number of food sources (population size) [6].

Scout bees generate new random solutions for abandoned food sources:[6]:

$$x_{ij}^{new} = x_j^{min} + r_j(x_j^{max} - x_j^{min}), r_j \sim \mathcal{U}(0,1),$$

Where x_j^{min} and x_j^{max} are the lower and upper bounds of parameter j[6].

4.4 Binary ABC Adaptation for Feature Selection

To adapt ABC for discrete binary feature selection, we employ a sigmoid-based transfer function [6][10]:

4.4.1 Neighbor Generation and Transfer

For each feature position j in food source i:

1. Generate continuous intermediate value using the neighbor formula [6]:

$$v_{ij} = b_{ij} + \phi_{ij}(b_{ij} - b_{kj}),$$

where $b_{ij}, b_{kj} \in \{0,1\}$ and $\phi_{ij} \sim \mathcal{U}(-1,1)$[6].

2. Apply sigmoid transfer function to map to probability [6][10]:

$$s(v_{ij}) = \frac{1}{1 + e^{-v_{ij}}}.$$

3. Threshold at probability 0.5 to obtain binary value [6][10]:

$$b'_{ij} = \begin{cases} 1, & s(v_{ij}) > 0.5, \\ 0, & \text{otherwise}. \end{cases}$$

This preserves the neighbor-based exploration mechanism of basic ABC while mapping to discrete binary values [6][10].

4.4.2 Greedy Selection

After generating a new candidate b_i'[6]:

- Evaluate $\mathrm{Fit}(b_i')$.
- If $\mathrm{Fit}(b_i') > \mathrm{Fit}(b_i)$: accept $b_i \leftarrow b_i'$ and reset trial counter to 0.
- Else: reject the new candidate and increment trial counter [6].

4.5 Basic ABC Algorithm Procedure

Algorithm 1: Binary ABC for Feature Selection

```
Input: Training data X with labels y, feature dimension D,
parameters: SN (population size), MaxCycles (max iterations),
limit (abandonment threshold), α, β (fitness weights)
Output: Optimal feature subset mask b*
// Initialization
1.  For i = 1 to SN:
      Generate random binary solution b_i ∈ {0,1}^D with P(b_ij = 1) = 0.5
      Evaluate Fit(b_i) using cross-validated classifier on selected features
      Initialize trial_i = 0
      End For
Store b* = argmax_i Fit(b_i) // Best solution so far
// Main Loop

2.  For cycle = 1 to MaxCycles:
  // Employed Bee Phase
  For each employed bee i = 1 to SN:
    Randomly select neighbor index k ≠ i
    For each feature j = 1 to D:
      Generate φ_ij ~ U(-1, 1)
      Compute v_ij = b_ij + φ_ij(b_ij - b_kj)
      Apply sigmoid: s(v_ij) = 1/(1 + exp(-v_ij))
      Threshold: b'_ij = (s(v_ij) > 0.5) ? 1 : 0
    End For

    Evaluate Fit(b'_i)
    If Fit(b'_i) > Fit(b_i):
      b_i = b'_i
      trial_i = 0
    Else:
      trial_i = trial_i + 1
    End If
    If Fit(b_i) > Fit(b*):
      b* = b_i
    End If
  End For  // End Employed Bee Phase

  // Onlooker Bee Phase
  Compute selection probabilities: p_i = Fit(b_i) / Σ Fit(b_m)

  For each onlooker bee:
    Select index i according to probability distribution p
    Repeat same neighbor generation and greedy update as employed phase
    Update b* if improved
  End For  // End Onlooker Bee Phase

  // Scout Bee Phase
  For each food source i = 1 to SN:
    If trial_i ≥ limit:
      Generate new random binary solution b_i
      Evaluate Fit(b_i)
      trial_i = 0
      If Fit(b_i) > Fit(b*):
        b* = b_i
      End If
    End If
  End For  // End Scout Bee Phase

End For // cycle
3.  Return b*
```

4.6 Algorithm Parameters and Implementation Details

The principal parameters of the Artificial Bee Colony (ABC) algorithm used in this study are summarized as follows [6][7]. The population size (SN), which corresponds to the number of food sources and employed bees, controls the trade-off between exploration capability and computational cost; typical values range from 20 to 40, and in this work SN=30 [6][7]. The maximum number of cycles (MaxCycles) defines the termination criterion of the algorithm and is commonly set between 100 and 200 iterations; here, MaxCycles=150 [6][7]. The abandonment limit (limit) specifies the maximum number of consecutive trials without improvement after which a food source is abandoned and the corresponding employed bee becomes a scout; values typically lie in the range of

10 20, and a value of limit=15 is adopted in this study [6][7]. To balance recognition performance and subset compactness, the fitness function weights are set to α=0.9, emphasizing classification accuracy, and β=0.1, imposing a mild penalty on feature subset size [7].

Feature Subset Evaluation

For each candidate binary feature subset b, the selected classifier (e.g., C4.5 or SMO) is trained using only the corresponding features, and its classification accuracy is estimated through 5-fold cross-validation on the training set. This procedure provides a reliable and unbiased assessment of feature subset quality for fitness evaluation within the ABC framework [4][7].

Integration into the Biometric Recognition System

The proposed ABC-based feature selection is integrated into the multimodal biometric system as follows [7]. First, training samples are collected for all three biometric traits across the selected benchmark databases. Multi-algorithm feature extraction is then performed for each modality, followed by feature-level fusion to generate high-dimensional training feature vectors x_{train}. The binary ABC algorithm is subsequently applied to the fused training data and corresponding labels to identify the optimal feature subset mask b^*. Both training and test feature vectors are then reduced using this mask, yielding $x_{\text{train},*}$ and $x_{\text{test},b*}$. Finally, the chosen classifier C4.5, SMO, or a Euclidean distance-based matcher is trained on the reduced training features and evaluated on the test set. System performance is assessed using standard biometric metrics, including recognition rate, false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER) [7].

V. EXPERIMENTAL SETUP

5.1 Biometric Databases and Multi-System Design

Table 1 summarizes the biometric databases used [7]:

Trait	Database	#Subjects	#Samples
Fingerprint	CASIA FP	1000	8000
Fingerprint	FVC 2002	110	880
Iris	CASIA V1.0	108	1080
Iris	IITD Iris	224	896
Palmprint	CASIA Palm	600	7200
Palmprint	IITD Palm	235	2350

Multi-Algorithmic Systems: Single-trait systems with multiple algorithms per trait (e.g., fingerprint using minutiae + texture) [7].

Multimodal Systems: Virtual person construction where each subject combines samples from different trait modalities and/or different databases [7]. For example, a virtual Fingerprint+Iris system combines one person's fingerprint from CASIA-FP with another person's iris from CASIA-Iris, creating enlarged virtual person databases [7].

5.2 Training and Testing Protocols

A stratified random train test split is adopted, with 50% of the samples used for training and the remaining 50% reserved for testing to ensure balanced class representation [7]. During the ABC-based feature selection process, 5-fold cross-validation is performed exclusively on the training set to estimate the classification accuracy Acc(b) for each candidate feature subset, thereby preventing information leakage and ensuring unbiased fitness evaluation [4][7]. All recognition results are reported at a fixed false acceptance rate (FAR) of 0.01, which is a commonly used operating point in biometric system evaluation [7].

5.3 Baseline Methods and Classifiers

To assess the effectiveness of the proposed approach, several feature reduction baselines are considered [7]. The No Feature Selection (No FS) baseline uses the full fused feature vector without dimensionality reduction and serves as a lower bound reference. Principal Component Analysis (PCA) is employed as a classical feature extraction baseline, retaining 80 90% of the total variance. In addition, a basic ABC based feature selection method from the literature is included for comparative analysis.

Performance evaluation is carried out using a diverse set of classifiers [7]. A Euclidean distance-based matcher is used as a simple reference baseline. The C4.5 decision tree classifier is included due to its ability to handle both discrete and continuous features. Sequential Minimal Optimization (SMO), implementing Support Vector Machines (SVMs), is employed for its effectiveness in high-dimensional feature spaces. Naive Bayes serves as a probabilistic baseline classifier, while Random Forests, as an ensemble learning method, are used to assess robustness and the ability to capture feature interactions.

5.4 Performance Metrics

System performance is evaluated using standard biometric recognition metrics [7]. The Recognition Rate (RR) denotes the percentage of test samples correctly classified. The False Acceptance Rate (FAR) measures the proportion of imposters incorrectly accepted, while the False Rejection Rate (FRR) quantifies the proportion of genuine users incorrectly rejected. The Equal Error Rate (EER) corresponds to the operating point where FAR equals FRR, with lower EER values indicating superior overall system performance. In addition, Receiver Operating Characteristic (ROC) curves are plotted to analyze the trade-off between FAR and the Genuine Acceptance Rate (GAR = 1 − FRR).

To quantify dimensionality reduction effectiveness, the feature reduction percentage is computed as

$$\text{Reduction}\backslash\% = \left(1 - \frac{\sum b_j}{D}\right) \times 100.$$

where D is the dimensionality of the original fused feature vector and b_j indicates whether the j-th feature is selected [7].

Finally, computational efficiency is assessed through two metrics [7]. Training time corresponds to the offline cost of running the ABC optimization during system enrollment, while testing time per sample measures the time required to classify an individual test sample using the trained model, which is critical for real-time biometric deployment.

VI. RESULTS AND DISCUSSION

6.1 Multi-Algorithmic Fingerprint Systems

Table 2 summarizes the feature dimensionality reduction results for the multi-algorithmic fingerprint systems under different feature reduction strategies [7]. The baseline approach without feature selection (No FS) retains the full 512-dimensional fused feature vector. Principal Component Analysis (PCA) achieves a substantial dimensionality reduction of approximately 90%, reducing the feature space to 51 dimensions. Both the basic ABC method and the proposed ABC-based feature selection approach reduce the feature dimensionality to 102 features, corresponding to an 80% reduction.

Table 2 presents feature dimensionality reduction for multi-algorithmic fingerprint systems

Method	Initial Dim	Reduced Dim	Reduction %
No FS	512	512	0%
PCA	512	51	90%
Basic ABC	512	102	80%
ABC (proposed)	512	102	80%

Table 3 reports the recognition performance of multi-algorithmic fingerprint systems using Euclidean distance-based matching [7]. For both MA-Finger1 and MA-Finger2 configurations, the proposed ABC-based method yields a marked improvement in recognition accuracy, achieving rates exceeding 96%, compared with approximately 84% for PCA and around 81 83% for the No FS baseline.

Table 3 shows recognition accuracy (Euclidean distance) for multi-algorithmic fingerprint

System	No FS (%)	PCA (%)	ABC (%)
MA-Finger1	82.5	84.0	96.5
MA-Finger2	80.8	82.3	96.2

These results demonstrate that, although PCA attains a higher level of dimensionality reduction, the ABC-based feature selection method consistently delivers significantly superior recognition performance while still achieving substantial feature space reduction. This highlights the effectiveness of the proposed ABC approach in identifying and retaining highly discriminative fingerprint features, thereby enhancing matching accuracy without incurring prohibitive dimensionality or computational costs [7].

Table 4 shows recognition accuracy with supervised classifiers (C4.5, SMO)

System	PCA +C4.5 (%)	ABC+C4.5 (%)	PCA+SMO (%)	ABC+SMO (%)
MA-Finger1	88.2	99.1	87.5	99.2
MA-Finger2	86.9	99.0	86.2	99.1

Table 4 presents the recognition performance of multi-algorithmic fingerprint systems using supervised classifiers, specifically C4.5 decision trees and SMO-based Support Vector Machines (SVMs) [7]. When combined with PCA-based dimensionality reduction, recognition accuracies range between approximately 86% and 88% across both MA-Finger1 and MA-Finger2 configurations. In contrast, the proposed ABC-based feature selection consistently achieves near-perfect recognition performance, with accuracies of approximately 99% for both classifiers and system configurations.

These results clearly indicate that ABC-selected feature subsets are significantly more discriminative than PCA-reduced features when used with supervised learning models. Unlike PCA, which retains features based on variance alone, the ABC-based wrapper approach explicitly optimizes classification performance, enabling it to capture complex, non-linear decision boundaries more effectively. Consequently, the proposed method demonstrates superior suitability for high-accuracy fingerprint recognition in multi-algorithmic biometric systems [7].

6.2 Multi-Algorithmic Iris Systems

Table 5 reports the feature dimensionality reduction results for the multi-algorithmic iris systems under different feature reduction strategies [7]. Without feature selection (No FS), the full 640-dimensional fused feature vector is retained. PCA achieves a 90% reduction, compressing the feature space to 64 dimensions, while both the basic ABC method and the proposed ABC-based approach reduce the dimensionality to 128 features, corresponding to an 80% reduction.

The recognition performance using Euclidean distance-based matching is presented in Table 6 [7]. Across all multi-algorithmic iris configurations (MA-Iris1 to MA-Iris3), the proposed ABC-based feature selection consistently delivers superior performance, achieving recognition accuracies of approximately 97%, compared with 82 84% for PCA and 80 82% for the No FS baseline.

Table 5 presents feature dimensionality reduction for iris

Method	Initial Dim	Reduced Dim	Reduction %
No FS	640	640	0%
PCA	640	64	90%
Basic ABC	640	128	80%
ABC (proposed)	640	128	80%

Table 6 shows recognition accuracy (Euclidean distance) for multi-algorithmic iris

System	No FS (%)	PCA (%)	ABC (%)
MA-Iris1	81.5	83.8	97.2
MA-Iris2	79.9	82.1	96.8
MA-Iris3	80.2	83.5	97.0

Table 7 summarizes the recognition accuracies obtained with supervised classifiers, namely C4.5 and SMO (SVM), using PCA- and ABC-reduced feature sets [7]. The ABC based method achieves consistently high recognition rates in the range of 99.1% 99.4% across all system configurations and classifiers. In contrast, PCA-based dimensionality reduction results in substantially lower accuracies, typically between 85% and 87%.

Table 7 shows recognition accuracy with supervised classifiers

System	PCA+C4.5 (%)	ABC+C4.5 (%)	PCA+SMO (%)	ABC+SMO (%)
MA-Iris1	86.9	99.3	86.5	99.4
MA-Iris2	85.2	99.2	85.8	99.3
MA-Iris3	85.5	99.1	86.1	99.2

Overall, these results demonstrate that ABC-based feature selection is highly effective for multi-algorithmic iris recognition, achieving strong discriminative performance with both distance-based and supervised classifiers while maintaining substantial feature space reduction. The consistently high recognition rates indicate that the selected feature subsets preserve critical iris texture information and enable robust class separation in high-dimensional fusion settings [7].

6.3 Multi-Modal Systems (Fingerprint + Iris + Palmprint)

Table 8 summarizes the feature dimensionality reduction results for the three-modal biometric system that integrates fingerprint, iris, and palmprint modalities [7]. The No FS baseline retains the full 1792-dimensional fused feature vector. PCA achieves a 90% reduction, compressing the feature space to 180 dimensions, while both the basic ABC method and the proposed ABC-based approach reduce the dimensionality to 256 features, corresponding to an 86% reduction.

The recognition performance using Euclidean distance-based matching for the three-modal system is reported in Table 9 [7]. For both system configurations, the ABC-based feature selection method substantially outperforms PCA and the No FS baseline, achieving recognition accuracies of approximately 97%, compared with 84 86% for PCA and 83 85% for the unreduced feature set.

Table 8 presents feature reduction for the 3-modal system combining all three traits

Method	Initial Dim	Reduced Dim	Reduction %
No FS	1792	1792	0%
PCA	1792	180	90%
Basic ABC	1792	256	86%
ABC (This Work)	1792	256	86%

Table 9 shows recognition accuracy (Euclidean distance) for 3-modal systems

System Configuration	No FS (%)	PCA (%)	ABC (%)
MM-Finger+Iris+Palm1	84.5	85.9	97.1
MM-Finger+Iris+Palm2	83.2	84.5	96.8

Table 10 presents the recognition accuracies obtained with supervised classifiers, specifically C4.5 and SMO (SVM), using PCA- and ABC-reduced feature representations [7]. The proposed ABC-based approach consistently attains recognition rates in the range of 99.0% 99.4% across all multimodal configurations and classifiers. In contrast, PCA-based dimensionality reduction yields accuracies below 88%, underscoring its limited ability to preserve class-discriminative information in highly fused multimodal feature spaces.

Table 10 shows recognition accuracy with supervised classifiers

System Configuration	PCA +C4.5 (%)	ABC +C4.5 (%)	PCA +SMO (%)	ABC +SMO (%)
MM-Finger+Iris+Palm 1	87.5	99.2	87.1	99.4
MM-Finger+Iris+Palm 2	86.8	99.0	86.5	99.3

These results confirm that the proposed ABC-based feature selection effectively identifies complementary and discriminative features across multiple biometric traits, enabling robust and highly accurate recognition in multimodal systems while maintaining substantial dimensionality reduction. The consistently high performance across both distance-based and supervised classifiers highlights the scalability and effectiveness of the proposed approach for large-scale multimodal biometric authentication [7].

6.4 Feature Reduction Summary

Table 11 provides a consolidated overview of feature dimensionality reduction achieved across all evaluated biometric system configurations [7]. For multi-algorithmic unimodal systems, PCA consistently reduces the feature space by approximately 88% 90%, while the proposed ABC-based feature selection achieves reductions in the range of 80% 82%. In multimodal configurations, PCA attains feature reductions of around 87% 90%, whereas ABC reduces dimensionality by approximately 84% for two-modal systems and 86% for the three-modal system.

Table 11 consolidates feature reduction across all systems

System Type	Initial Dim	PCA Reduction	ABC Reduction
Multi-Algo Finger	512	90%	80%
Multi-Algo Iris	640	90%	80%
Multi-Algo Palm	768	88%	82%
2-Modal (Any Pair)	1152 1280	87%	84%
3-Modal (All Traits)	1792	90%	86%

Several important observations can be drawn from these results [7]. First, ABC-based feature selection consistently achieves substantial dimensionality reduction (80% 86%) across all unimodal, multi-algorithmic, and multimodal systems. Second, although PCA yields slightly higher dimensionality reduction, this advantage comes at the cost of significantly degraded recognition performance, as demonstrated in the preceding sections. Finally, the proposed ABC-based approach offers a more favorable accuracy efficiency trade-off, combining moderate feature space reduction with consistently superior recognition accuracy in the range of 97% 99.4%.

Overall, these findings confirm that wrapper-based ABC feature selection is more effective than variance-based PCA for high-dimensional feature-level fusion in biometric systems, particularly when recognition accuracy is the primary performance objective [7].

6.5 Computation Time Analysis

Table 12 compares the computational costs of different feature reduction strategies in terms of training time and testing time per sample [7]. The No FS baseline requires approximately 5 minutes of training and incurs a testing time of 15 ms per sample. PCA significantly reduces the training time to about 2 minutes and lowers the testing time to 8 ms per sample. In contrast, the proposed ABC-based feature selection requires a substantially longer training time of approximately 45 minutes, reflecting the iterative nature of the evolutionary optimization process.

Table 12 compares computation times

Method	Training Time (min)	Test Time per Sample (ms)
No FS	5 min (baseline)	15 ms
PCA	2 min	8 ms
ABC	45 min	5 ms

Despite its higher training cost, the ABC-based approach achieves the lowest testing time, requiring only 5 ms per sample, owing to the substantial reduction in feature dimensionality. This reduction directly translates into faster classification during system operation. From a practical standpoint, testing time is the critical performance factor in real-world biometric applications such as access control, automated border control, and large-scale identity verification, where rapid response is essential.

Importantly, the increased training time associated with ABC-based feature selection is incurred only once during the offline enrollment phase, making it acceptable in practical deployments. The resulting reduction in testing time enables efficient real-time authentication, highlighting a favorable trade-off between offline optimization cost and online system performance. These results demonstrate that the proposed ABC-based approach is well suited for operational biometric systems where accuracy and real-time responsiveness are paramount [7].

VII. CONCLUSION AND FUTURE WORK

7.1 Conclusions

This work presented a comprehensive multi-algorithm, multimodal biometric person authentication framework that employs a basic Artificial Bee Colony (ABC) based feature selection strategy at the feature-level fusion stage [6][7]. By jointly exploiting multiple biometric traits and complementary feature representations, the proposed approach effectively addresses the inherent limitations of unimodal biometric systems.

The major contributions and findings of this study can be summarized as follows:

1. Multimodal, multi-algorithm system design: A robust authentication framework integrating fingerprint, iris, and palmprint modalities was developed, with multiple feature extraction algorithms applied to each trait to enhance complementary discriminatory information.
2. Binary ABC-based feature selection: The basic ABC algorithm was successfully adapted for discrete binary feature subset optimization using a sigmoid-based transfer function and greedy selection, while preserving the core neighborhood-based exploration and exploitation mechanisms of the original formulation [6][7].
3. Wrapper-based fitness formulation: A classifier-driven fitness function was designed to jointly optimize recognition accuracy and feature subset compactness, ensuring that selected features are directly aligned with classification performance.
4. Extensive experimental validation: The proposed method was evaluated on standard benchmark databases (CASIA, IITD, and FVC) using both distance-based matching (Euclidean distance) and multiple supervised classifiers (C4.5, SMO, Naive Bayes, and Random Forest), consistently outperforming PCA-based and baseline feature reduction approaches.
5. Strong performance outcomes:

- Recognition accuracies of 96.5% 97.5% using Euclidean distance and 99.0% 99.4% using supervised classifiers were achieved.
- Feature space reduction of 80% 86% was consistently obtained across unimodal, multi-algorithmic, and multimodal systems.
- Testing time of approximately 5 ms per sample enables real-time authentication.
- The proposed ABC-based approach demonstrates a superior accuracy efficiency trade-off compared with variance-based PCA and unreduced feature sets.
- Practical relevance: The proposed framework and ABC-based optimization procedure are well suited for deployment in large-scale biometric authentication systems, where high recognition accuracy, computational efficiency, and real-time responsiveness are critical requirements.

Overall, the results confirm that wrapper-based ABC feature selection is highly effective for managing high-dimensional feature-level fusion in multimodal biometric systems, yielding both high recognition performance and practical computational efficiency.

7.2 Future Work

Several promising directions can be explored to further enhance the proposed framework:

- Advanced ABC variants: Investigating improved ABC formulations with enhanced exploration and convergence behavior, such as Θ-ABC or hybrid ABC-based models.
- Deep learning integration: Incorporating CNN-based or transformer-based feature extraction with ABC-driven feature selection for end-to-end multimodal learning.
- Presentation attack detection: Extending the framework to incorporate liveness detection and spoof resistance at the feature or fusion level.
- Additional biometric traits: Expanding the multimodal architecture to include face, voice, vein, or gait biometrics.
- Cancelable biometrics: Developing revocable and renewable feature representations to enhance template security and resilience against compromise.
- Large-scale deployment: Evaluating scalability on large, real-world biometric datasets involving millions of users.
- Privacy-preserving authentication: Integrating secure computation techniques, such as homomorphic encryption or secure multi-party

computation, to enable privacy-aware biometric matching.

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