

Development of a Tent-Map-Enhanced Chaotic Grey Wolf Optimizer for Feature Selection in a Bimodal Face–Fingerprint Biometric Authentication System

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Abstract: Differences in feature dimensionality, quality, and reliability can cause face and fingerprint recognition methods to contribute unequally in a bimodal biometric classification system. This study proposes a Tent-map-enhanced Chaotic Grey Wolf Optimizer (ECGWO) for feature selection in a combined face–fingerprint biometric authentication system. Rather than using the random vectors in the standard Grey Wolf Optimizer (GWO) position-update process, the proposed approach uses two separate Tent-map chaotic sequences and applies chaotic modulation to balance exploration and exploitation. The algorithm extracts Local Binary Pattern (LBP) descriptors from the preprocessed face and fingerprint images, then normalizes and combines them. The ECGWO algorithm then identifies a small, discriminative feature subset. A V-shaped transfer function converts the continuous wolf positions into binary decisions for feature selection, and the fitness function simultaneously reduces both classification error and the number of selected features, with weights set at $\alpha = 0.9$ and $\beta = 0.1$. The selected feature subset is then classified using a Support Vector Machine (SVM). At a decision threshold of 0.51, the ECGWO-SVM method produced 140 true positives, 10 false negatives, 7 false positives, and 143 true negatives, resulting in an accuracy of 94.33%, a false acceptance rate (FAR) of 4.67%, a false rejection rate (FRR) of 6.67%, an F1-score of 94.28%, and an optimization time of 90.09 s. Under the reported experimental conditions, ECGWO-SVM achieved better classification performance and lower error rates than standard GWO-SVM.

Keywords: Grey Wolf Optimizer, Tent Map; Feature Selection, Bimodal Biometrics, Face Recognition, Fingerprint Recognition, Support Vector Machine.

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I. INTRODUCTION

Multimodal biometric systems combine evidence from multiple biometric traits to enhance recognition reliability and reduce reliance on a single source. In bimodal face–fingerprint systems, modalities may contribute unequally because of differences in representation quality, dimensionality, redundancy, and discriminative power. Without appropriate normalization and feature selection, these disparities can increase computational demands, promote overfitting, and introduce bias toward one modality (Dipti & Sandesh, 2026; Lukman & Priyadi, 2024).

Feature selection is therefore treated as a central component of the proposed system. It removes redundant or weak fused features while retaining information that supports accurate discrimination between genuine users and impostors. Grey Wolf Optimization (GWO) is a population-based metaheuristic inspired by the leadership hierarchy and cooperative hunting behaviour of grey wolves (Mirjalili et al., 2014). Although GWO offers a simple search mechanism and a useful balance between exploration and exploitation, it can converge prematurely or become trapped in local optima within high-dimensional search spaces.

Chaos-enhanced optimization replaces or perturbs conventional stochastic components with deterministic

chaotic sequences. The Tent map is attractive because of its ergodic behaviour and relatively uniform coverage of the interval (0,1). This study integrates Tent-map sequences into the GWO update mechanism to form an Enhanced Chaotic Grey Wolf Optimizer (ECGWO). The objective is to improve population diversity and the exploration–exploitation transition during binary feature selection for a fused face–fingerprint representation.

The principal contribution of this work is a Tent-map-based ECGWO feature-selection framework that: (i) replaces the standard GWO random vectors used to construct the coefficient vectors with two independent chaotic sequences; (ii) maps continuous search positions to binary feature-selection decisions using a V-shaped transfer function; (iii) balances SVM classification error against feature-subset size with a weighted fitness function; and (iv) compares the resulting ECGWO-SVM system with standard GWO-SVM across several decision thresholds using FAR, FRR, F1-score, accuracy, and optimization time.

II. RELATED WORK

Recent work has modified GWO through population adaptation, hybridization, opposition strategies, and other search-control mechanisms to improve convergence and feature selection. Wang et al. (2023) proposed a Population Adaptation-based Binary Grey Wolf Optimizer (PA-BGWO) that utilizes adaptive individual updating, head-wolf refinement, and feature-weight-guided mutation. Their experiments showed that the method could select compact subsets while maintaining strong classification performance over standard datasets.

Qais *et al.* (2023) combined GWO with SVM for anomaly detection in solar power plants, illustrating GWO's broader usefulness intended for optimizing SVM-based decision systems. Although the application differs from biometrics, the study shows that GWO search is compatible with SVM classification.

Guangwei *et al.* (2024) combined Golden Jackal Optimization and GWO for high dimensional feature selection, while Zhiwei *et al.* (2024) investigated a hybrid GWO-based approach for the same task. These studies reflect continuing efforts to improve search diversity and convergence in feature-selection problems.

Khaseeb *et al.* (2025) proposed improved binary GWO approaches which combine GWO and Particle Swarm Optimization. Their results show that hybrid search can improve feature-selection performance, but it can also increase algorithmic complexity. The present study follows a different direction: rather than adding a second population optimizer, it introduces deterministic Tent-map chaos through the GWO update process and evaluates the resulting ECGWO for bimodal biometric feature selection.

III. MATERIALS AND METHODS

The developed system follows the sequence: biometric acquisition, preprocessing, LBP feature extraction, feature normalization and fusion, ECGWO-based feature selection, SVM classification, user decision, and performance evaluation. Figure 1 shows the overall workflow.

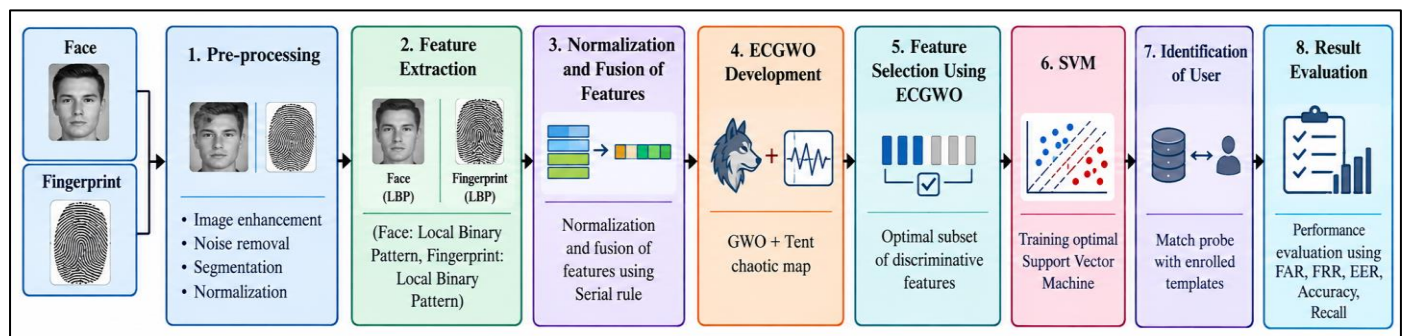


Fig 1 Processing Pipeline of the Proposed Bimodal Face–Fingerprint Biometric System.

➤ Acquisition of Biometric Traits

The experiment utilized biometric data from 300 subjects in the LAUTECH database. Multimodal biometric samples were collected to evaluate the proposed ECGWO-SVM model. A *k*-fold cross-validation protocol was implemented to maximize data utilization and maintain separation between model development and evaluation. In each fold, data were partitioned into training and validation sets; the model was trained on (*k*-1) folds, with the remaining fold serving as the validation set. This process was repeated until each observation was used once for validation. All data-dependent procedures, including preprocessing, ECGWO-based feature selection, and Support Vector Machine (SVM) hyperparameter optimization, were conducted exclusively on

the training folds to prevent data leakage. Only the held-out fold was used for performance evaluation. Model performance was averaged across the *k* validation folds to provide an overall estimate of effectiveness. In this protocol, all observations contribute to both training and evaluation, but the model does not assess its own training data in any iteration.

➤ Preprocessing

Biometric images underwent preprocessing steps including cropping, resizing, grayscale conversion, and histogram equalization to minimize irrelevant variation and enhance consistency. Each grayscale image was represented as a matrix in MATLAB. Feature normalization was

performed prior to fusion to prevent numerical scale differences between face and fingerprint representations from dominating the combined feature vector. The dataset consisted of JPEG face and fingerprint images, with original resolutions standardized to 128×128 pixels during preprocessing. Face images, initially in RGB format, were

converted to grayscale and captured frontally under controlled indoor illumination against a uniform background. Fingerprint images were grayscale JPEGs obtained from the left index finger using an optical scanner, ensuring clear ridge visibility and minimal noise. Figure 2 presents examples of images enhanced through histogram equalization.

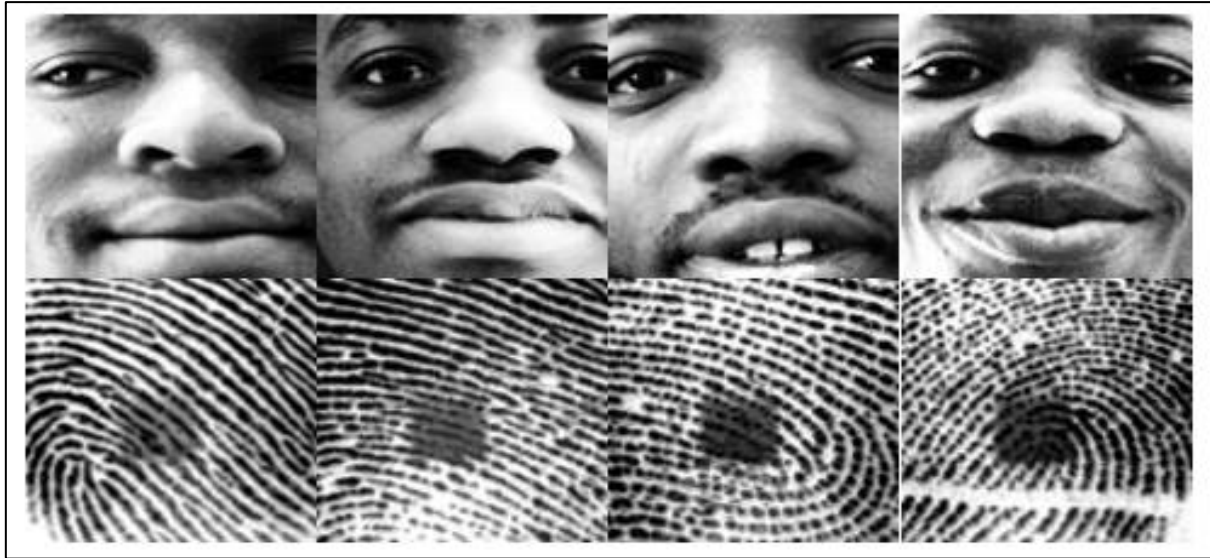


Fig 2 Samples of Enhanced Images Using Histogram Equalization

➤ Feature Extraction

Local Binary Pattern (LBP) descriptors were used for both face and fingerprint images. For each pixel neighborhood, the center pixel serves as the threshold for its neighbors. Neighbor values are compared with the center value and encoded as binary decisions; the resulting binary pattern is converted into an LBP code. When a sampling point does not coincide exactly with an image pixel, bilinear interpolation is used. The extracted LBP representations form the modality-specific feature vectors used in the subsequent fusion stage.

➤ Feature Normalization and Fusion

Let F_i denote the normalized feature vector associated with modality i and w_i its fusion weight. A weighted feature-level fusion can be expressed as:

$$F = \sum_{i=1}^n w_i F_i, \quad \sum_{i=1}^n w_i = 1 \quad (1)$$

Where $n = 2$ for the face and fingerprint modalities. The fused representation is subsequently presented to the feature-selection stage. The same normalization and fusion procedure is applied consistently before comparing GWO and ECGWO.

➤ Grey Wolf Optimization and the Proposed ECGWO

GWO models four leadership levels: alpha (α), beta (β), delta (δ), and omega (ω). The three best candidate solutions guide the remaining wolves. For a wolf position X , the standard encircling and leader-guided update can be written as:

$$D\alpha = |C_1 X\alpha - X|, \quad D\beta = |C_2 X\beta - X|, \quad D\delta = |C_3 X\delta - X| \quad (2)$$

$$X_1 = X\alpha - A_1 D\alpha, \quad X_2 = X\beta - A_2 D\beta, \quad X_3 = X\delta - A_3 D\delta \quad (3)$$

$$X(t+1) = (X_1 + X_2 + X_3) / 3 \quad (4)$$

$$A = 2ar_1 - a, \quad C = 2r_2 \quad (5)$$

In standard GWO, a decreases from 2 to 0 over the optimization process, while r_1 and r_2 are random vectors in $[0,1]$. The magnitude of A controls the transition between exploration and exploitation.

• Tent Chaotic Map

The Tent map is a one-dimensional deterministic chaotic map. For $u_i \in (0,1)$, it is defined as:

$$u_{i+1} = 2u_i, \quad \text{if } u_i < 0.5; \quad u_{i+1} = 2(1 - u_i), \quad \text{if } u_i \geq 0.5 \quad (6)$$

The initial value u_0 is selected from $(0,1)$, excluding values that generate degenerate short cycles. Two independent Tent-map sequences are maintained for the coefficient calculations.

• Tent-Chaos Enhancement

The proposed ECGWO substitutes two independent Tent-map values $u_i^{(1)}$ and $u_i^{(2)}$ for the standard random vectors in the coefficient calculation:

$$A = 2a \cdot u_i^{(1)} - a, \quad C = 2u_i^{(2)} \quad (7)$$

The chaotic sequence further modulates the convergence factor, introducing a nonlinear exploration–exploitation transition.

• Binary Feature Selection and Fitness Function

Each wolf represents a candidate subset over the D fused features. A V-shaped transfer function maps each continuous coordinate to a selection probability:

$$T(X_{i,j}) = |\tanh(X_{i,j})| \quad (8)$$

$$X_{i,j}^{\text{bin}} = 1 \text{ if } \text{rand} < T(X_{i,j}); \text{ otherwise } 0 \quad (9)$$

The fitness function balances classification error and subset size:

$$\text{Fitness} = \alpha \cdot \text{Error_rate}(X^{\text{bin}}) + \beta \cdot (|S|/D), \quad \alpha + \beta = 1 \quad (10)$$

Where $|S|$ is the number of selected features. The study uses $\alpha = 0.9$ and $\beta = 0.1$, placing greater emphasis on classification performance while still penalizing unnecessarily large subsets.

• ECGWO Procedure

- ✓ Step 1: Initialize N wolf positions in the D -dimensional search space and initialize the Tent-map sequences.
- ✓ Step 2: Evaluate each candidate subset using Equation (10) and identify the alpha, beta, and delta solutions.
- ✓ Step 3: Generate/update the two independent Tent-map sequences.
- ✓ Step 4: Update the ECGWO coefficient vectors and the convergence-control term used by the implementation.
- ✓ Step 5: Update wolf positions using the alpha, beta, and delta leaders.
- ✓ Step 6: Apply the V-shaped transfer function and binary conversion to obtain candidate feature subsets.
- ✓ Step 7: Re-evaluate fitness and update the three leaders.
- ✓ Step 8: Repeat until the maximum iteration count or implemented stopping condition is reached, then return the alpha solution as the selected feature subset.

➤ Classification Using Support Vector Machine

Each feature subset selected by the optimizer was used to train a Support Vector Machine (SVM) classifier. To ensure a fair comparison, both GWO-SVM and ECGWO-SVM configurations utilized identical data partitions and classifier settings. The classification stage was implemented in MATLAB 2023a with an SVM employing a Radial Basis Function (RBF) kernel. The SVM penalty parameter (C) and RBF kernel parameter (γ) were jointly optimized alongside

the feature-selection mask using the Enhanced Chaotic Grey Wolf Optimization (ECGWO) algorithm. During ECGWO optimization, candidate solutions were evaluated based on k -fold cross-validation classification loss, with an additional penalty applied for the proportion of selected features. This approach enabled simultaneous optimization of classification performance and feature-subset compactness.

➤ Implementation Environment

The experiments were conducted in MATLAB R2023a on a Dell 7250 computer running Windows 11 Professional 64-bit, with an Intel Core i5 vPro processor at 2.4 GHz, 16 GB RAM, and a 1 TB hard disk drive.

➤ Evaluation Measures

For the reported confusion matrices, a legitimate user is the positive class and an impostor is the negative class. The principal measures are defined as follows:

$$\text{FAR} = \text{FP} / (\text{FP} + \text{TN}) \times 100\% \quad (11)$$

$$\text{FRR} = \text{FN} / (\text{FN} + \text{TP}) \times 100\% \quad (12)$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (13)$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (14)$$

$$\text{F1} = 2(\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (15)$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \times 100\% \quad (16)$$

Equal Error Rate (EER) is the operating point at which FAR and FRR are equal, or approximately equal after interpolation. Because only four decision thresholds are reported, the present paper does not claim a precise EER value from the coarse threshold grid. Optimization time is the wall-clock time required for the feature-selection procedure under the stated computing environment.

IV. RESULTS AND DISCUSSION

Table 1 compares standard GWO-SVM and ECGWO-SVM at decision thresholds of 0.10, 0.31, 0.41, and 0.51. Across all four reported thresholds, ECGWO-SVM achieved higher accuracy and F1-score and lower FAR and FRR than GWO-SVM. The best reported ECGWO-SVM accuracy occurred at threshold 0.51.

Table 1 Classification Performance of GWO-SVM and ECGWO-SVM.

Threshold	Method	TP	FN	FP	TN	FAR (%)	FRR (%)	F1 (%)	Accuracy (%)	Time (s)
0.10	GWO	140	10	17	133	11.33	6.67	91.21	91.0	98.23
0.10	ECGWO	143	7	15	135	10.0	4.67	92.86	92.67	89.77
0.31	GWO	139	11	15	135	10.0	7.33	91.45	91.33	96.56
0.31	ECGWO	142	8	12	138	8.0	5.33	93.42	93.33	89.77
0.41	GWO	138	12	13	137	8.67	8.0	91.69	91.67	96.02
0.41	ECGWO	141	9	9	141	6.0	6.0	94.0	94.0	89.7
0.51	GWO	137	13	10	140	6.67	8.67	92.26	92.33	96.81
0.51	ECGWO	140	10	7	143	4.67	6.67	94.28	94.33	90.09

At a threshold of 0.51, GWO-SVM produced TP of 137, FN of 13, FP of 10, and TN of 140. These values correspond to an FAR of 6.67%, an FRR of 8.67%, an F1-score of 92.26%, and an accuracy of 92.33%, with an optimization time of 96.81 s. Under the same reported threshold, ECGWO-SVM produced TP of 140, FN of 10, FP of 7, and TN of 143, corresponding to FAR of 4.67%, FRR of 6.67%, F1-score of 94.28%, accuracy of 94.33%, and an optimization time of 90.09 s.

Relative to GWO-SVM at threshold 0.51, ECGWO-SVM increased accuracy by 2.00 percentage points and F1-score by 2.02 percentage points, while reducing FAR by 2.00 percentage points and FRR by 2.00 percentage points. The measured optimization time was 6.72 s lower in the reported run.

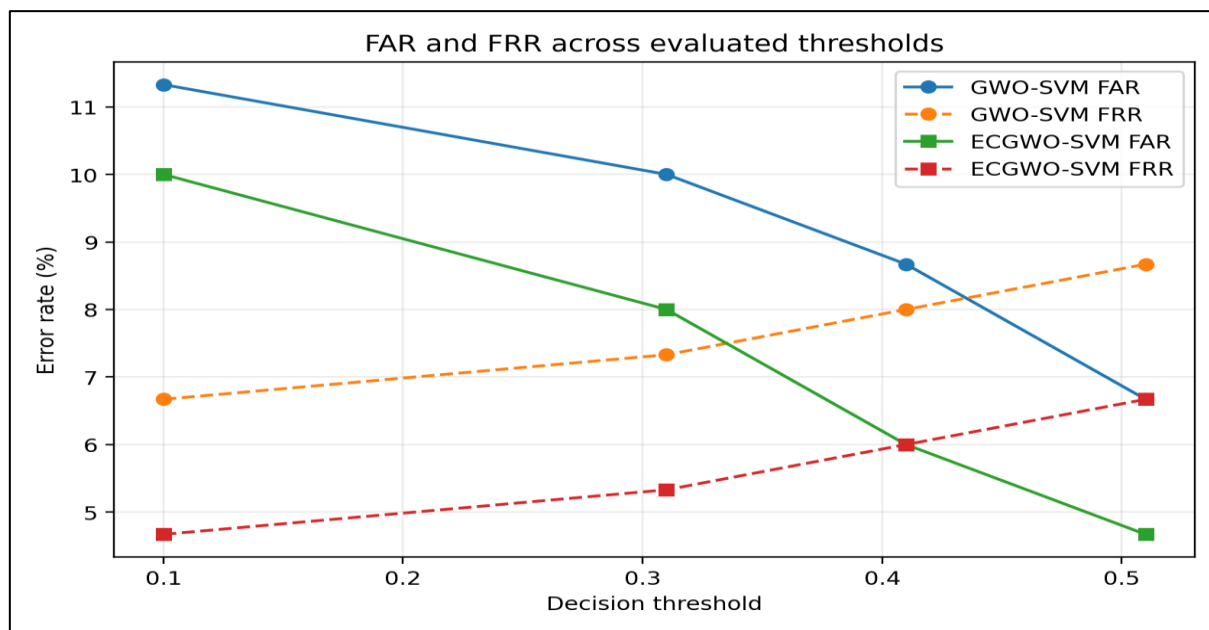


Fig 3 FAR and FRR Across the Evaluated Decision thresholds for GWO-SVM and ECGWO-SVM.

Figure 3 shows the trade-off between false acceptance and false rejection as the decision threshold changes. For ECGWO-SVM, FAR and FRR are both 6.00% at threshold 0.41; therefore, among the sampled operating points, 0.41 is the observed equal-error operating point with EER of 6.00%. A denser threshold sweep would be preferable for estimating an interpolated EER more precisely. For GWO-SVM, the FAR and FRR curves cross between the sampled thresholds 0.31 and 0.41, so a precise GWO EER should not be reported without interpolation along with a finer threshold sweep.

V. CONCLUSION AND FUTURE WORK

This study developed an Enhanced Chaotic Grey Wolf Optimizer (ECGWO) for binary feature selection, addressing the chaotic grey wolf optimization (CGWO) problem using a tent-map chaotic sequence within a face–fingerprint bimodal biometric authentication system. The approach incorporated LBP-based feature vectors, feature normalization and fusion, ECGWO-based subset search, and support vector machine classification. The feature-selection objective minimized both classification error and the proportion of features retained.

The results demonstrate that ECGWO-SVM consistently outperformed standard GWO-SVM across the four evaluated thresholds. At threshold 0.51, ECGWO-SVM achieved 94.33% accuracy, 94.28% F1-score, 4.67% FAR,

and 6.67% FRR, compared to 92.33% accuracy, 92.26% F1-score, 6.67% FAR, and 8.67% FRR for GWO-SVM. ECGWO also achieved a lower optimization time in the reported experiment. These findings suggest that Tent-map-based search diversification enhances the GWO feature-selection process under the tested experimental conditions.

Subsequent studies should evaluate the method on independent public biometric datasets, report subject-disjoint training and testing protocols, conduct repeated-run statistical tests, quantify the number and percentage of selected features, conduct ablation experiments on the chaotic components, and assess robustness under image-quality degradation and presentation attacks. Additional biometric modalities and real-time deployment scenarios may also be investigated.

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