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ABCGSA: A Novel Hybrid Artificial Bee Colony Gravitational Search Algorithm for Feature Selection of Fingerprint Intramodal Biometric System

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Abstract: The feature selection (FS) algorithm extracts the most relevant and significant data from the large-dimensional feature space in the dataset, enhancing the biometric system's classification accuracy. However, optimizing the feature diversity of high-dimensional feature space of the FS algorithm has been given little attention in existing FS algorithms. Therefore, a hybrid artificial bee colony (ABC)-based disruptive selection and Gravitational Search Algorithm (GSA) to form ABCGSA for enhanced FS prior to the classification phase of Fingerprint Intramodal Biometric System (FIBS) was developed. The developed ABCGSA was used to select optimal feature sets during FS to enhance the sensitivity, recognition accuracy (RA), false positive rate (FPR), false negative rate (FNR), and recognition time (RT) of FIBS. When compared with the existing algorithms used for FS, the results showed that ABCGSA's sensitivity and RA increased by 3.21% and 4.73%, while FPR and FNR decreased by 8.96% and 3.21%, and RT improved by 20 s, thus enhancing the efficacy of FIBS. The developed algorithm could be used for FS of an intramodal biometric system to enhance access control in facilities.

Keywords: feature selection, ABC, GSA, Fingerprint Intramodal Biometric System (FIBS), pattern recognition

1. Introduction

An authentication system that relies on a single biometric information is called a unimodal biometric system (UBS). Intra-class variation, inter-class similarities, noise in sensed data, non-universality, and spoof attacks are some of the limitations encountered by UBS that is developed using fingerprint [1]. The biometric system's performance is usually poor due to the increased false positive rate (FPR) and false negative rate (FNR) caused by these limitations [2]. Achieving the needed performance in real-time applications in systems that require robust authentication particularly, it is therefore clear that UBS is insufficient. Overcoming some of the limitations of UBS, multibiometrics, which is the combination of multiple sources of biometric information for precise authentication, is frequently regarded as a means [3].

Merging of the retrieved features from the same modality (intramodal) or different modalities (intermodal) can be done using feature fusion in a multibiometric system. A UBS can be made to work better by mitigating some of its shortcomings through intramodal fusion of retrieved features from fingerprint at score layer fusion [4]. However, unlike feature-level fusion, the details collected for score layer merging are limited due to information loss at higher levels, which may result in poor outcomes [2].

A high-dimensional feature space is produced by feature-level fusion because of the massive dimension of the merged feature vectors, which could include unnecessary and duplicated data. The high dimensionality of the feature space in the dataset, which results

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from having a lot of redundant and irrelevant features, affects the computational complexity and classification accuracy of the intramodal biometric system (IBS). When performing extraction of feature or feature selection (FS), fusing at the feature level is possible [3]. For effective evaluation of this high-dimensional, multivariate information, scholars should concentrate on FS [4, 5]. FS is a way of selecting the features with the greatest value of a collection of attributes that establish patterns in a dataset. Subset FS tries to lower a dataset of high-dimensional computational complexity by decreasing the number of attributes needed to describe it; hence, the effectiveness of the learning algorithm was improved on a particular task at hand. Furthermore, huge feature vectors increase the cost of storage and classification time [1].

Attribute concatenation or weighted summation techniques are utilized in the feature extraction phase, while nature-inspired algorithms could be used during the FS phase [2]. Nature-mimic optimization algorithms like Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), ABC, and Gravitational Search Algorithm (GSA) can be utilized in the FS phase. ABC is a nature-inspired algorithm that operates on the intelligent food-gathering behavior of honeybee swarms [6]. The ABC method has many benefits, including simplicity, robustness, rapid convergence, and high adaptation [6, 7]. Using shared intelligence, they simulate a self-organized society collaborating to achieve a shared objective, such as resource gathering [8]. However, it has the disadvantage of early convergence in the latter search phase, and the optimal solution cannot sometimes be found. GSA is a stochastic optimization algorithm that operates on Newton's gravitational and motion laws. GSA's global movement ensures the exploitation phase in GSA [2, 9, 10]. The steps to achieving the aim of the paper are:

"To carry out a background study and inform the literature review with regard to hybridization of ABC based on disruptive selection with GSA for FS of extracted texture features from locally acquired fingerprints in order to improve the efficiency of Fingerprint Intramodal Biometric System (FIBS)".

"To propose a novel technique titled Hybrid ABCGSA for FS to enhance the efficiency of classification by picking only relevant and useful information from extracted feature sets being an optimization problem. The novelty of the proposed technique will be demonstrated in an enhanced efficiency of FIBS".

"To test and validate the proposed methodology on various performance metrics such as sensitivity, recognition accuracy (RA), and decrease in FPR, FNR, and recognition time (RT)".

"To compare the proposed methodology with existing techniques such as ABC and GSA".

The organization of the paper is as follows: Section 1 is the introduction. Section 2 contains the literature review. Section 3 depicts the materials and methods for the developed ABCGSA, and Sections 4 and 5 contain experimentation, results, and analysis as well as conclusion and future work, respectively.

2. Literature Review

Yildizdan and Baykan [11] developed a Hybrid BA_ABC Algorithm for Global Optimization Problems. To improve the search capability of the Bat Algorithm (BA), inertia weight was first added to the speed formula in the study. A new algorithm that operates in a hybrid manner with the ABC algorithm, whose diversity and global search capability are stronger than the BA, was then proposed.

In reference to Abdullah et al. [12], a multimodal palmprint biometric system was developed by performing the feature-level fusion of the left and right palmprint images to obtain an optimal recognition rate. To extract the features, a modified multilobe ordinal filter was used. This results in a high-dimensional feature vector that requires larger memory to store.

In reference to Oluyinka et al. [13], the feature-level fusion of Face, Iris, and Fingerprints was performed by employing the Modified Clonal Selection Algorithm (MCSA). Which is characterized by feature-balance maintenance capability and low computational complexity are characteristics of the developed and implemented MCSA for feature-level fusion. Rather than using random selection, tournaments among neighbors were performed to modify the standard Tournament Selection Method (TSM) in order to reduce the between-group selection pressure associated with the standard TSM. The Modified Tournament Selection Method was incorporated into its selection phase to formulate CSA. The systems fused with MCSA have a higher RA than those fused with CSA, also with a lower RT, as shown by quantitative experimental results.

Rajeshwari and Rathika [14] presented palm print recognition using image processing techniques. An image was resized and converted into another color space during the preprocessing stage to improve the efficiency of image recognition. The retrieved images were enhanced with the help of a Gaussian filter after preprocessing. To detect the edges of an image, the Laplacian of Gaussian technique is used. Feature extraction methods such as Gray Level Co-occurrence Matrix and Shape and Merged (Texture and Shape) methods were used to extract features from the images.

Assouma et al. [15] utilized an artificial intelligence method, through which a biometric fingerprint recognition system was developed. Fingerprint image acquisition, feature extraction, and comparison or matching were the three main structured steps used in the methodology. Non-contact fingerprint images were used for training the recognition model to allow the developed system to work without contact. A database of 19 individuals, each having 15 fingerprint images acquired without contact, was used.

Chaudhary [16] developed a revised algorithm (Modified Artificial Bee Colony Algorithm With Selection Strategy (MABC-SS)) derived from the artificial bee colony (ABC) optimization algorithm. The terms of alteration included population initialization, search equations, strategies, and strategy selection techniques. The algorithm's population initialization was executed utilizing random and opposition-based learning methodologies. The algorithm's search equations and techniques emphasize exploration and exploitation, specifically seeking solutions in proximity to a local or global optimum. The Wilcoxon sum ranking test corroborates that MABC-SS attained statistically significant results in 48% of the classical and 70% of the CEC2019 benchmark test functions relative to the original ABC.

In reference to Fan et al. [17], to mitigate the interference of superfluous features on the support tensor train machine, enhance training efficiency, and augment the model's classification performance, a step gravitational search strategy was devised. The algorithm established a novel dual population structure utilizing a step function, wherein the subpopulations Pop1 and Pop2 concentrate on exploration and exploitation, respectively, thereby circumventing the limitations of the conventional single population structure that struggles to balance these two aspects.

In reference to Etminaniesfahani et al. [18], to achieve strong exploration and highly efficient exploitation capabilities, the hybridization of the ABC with the Fibonacci indicator algorithm was proposed. It was shown that the hybrid algorithm outperformed ABC and Fibonacci Indicator Algorithm (FIA) and delivered superior outcomes for various optimization functions.

Rostami et al. [4] conducted a comparative analysis and classification of various FS techniques. The study examined wrapper and filter SI-based approaches, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Differential Evolution (DE), Gravitational Search Algorithm (GSA), Firefly Algorithm (FA), Bat Algorithm (BA), Cuckoo Optimization Algorithm (COA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Salp Swarm Algorithm (SSA), in the context of FS. Additionally, the advantages and disadvantages of the various examined swarm intelligence-based FS techniques are assessed.

Lamia and Ben Amara Najoua [19] proposed multi-instance fusion with degraded context. The purpose of the described approach was to identify fingers that would improve recognition results and fuse them at the score level, with fuzzy measurements defined using the Choquet integral and PSO. The fusion produced an Equal Error Rate (EER) of 0.22%. These results showed that fusing at the matching scores stage of the three unimodal systems considerably improves identification accuracy. The biometric data collected for fusion at the score level were limited.

Bindu and Sabu [20] proposed a hybrid FS technique utilizing ABC and GA. The proposed technique hybridized ABC and GA, with the aim that the combination of the two algorithms can further optimize their effectiveness. The presented technique recommended swapping populations from ABC and GA after each cycle. The presented technique prevented ABC's local optima stagnation by generating population diversity from GA at each cycle. The merging technique's results showed that GA compensates for ABC's shortcomings. In the simulation, a classification algorithm based on Random Forests was utilized. The accuracy of the classification following tenfold cross-validation was utilized to evaluate the training algorithm's efficiency. An exceptional finding from the presented technique shows that hybridization increased the efficiency of the ABC algorithm for FS. The selection of important attributes resulted in higher accuracy of classification. Also, it selected fewer features than the previous FS method, which used ABC. On large-dimensional feature sets, however, no optimization of the hybrid approach was addressed.

Jooda et al. [1] presented an ABC technique for FS of texture features extracted from many fingerprint instances to increase FIBS efficiency. At the threshold values, ABC-based FIBS raised sensitivity by 1.87%, RA by 2.75%, FPR by 5.21%, FNR by 1.87%, and RT by 50 s when compared to UBS readings. The results demonstrated that FIBS and UBS performed significantly better in terms of sensitivity, RA, FPR, and FNR performance despite lowering the system's feature set. The gains were made possible by removing redundant and irrelevant attributes from fingerprint image-derived features. However, there is a need to improve the exploitation capabilities by combining a local search algorithm with ABC to optimize FS and improve the sensitivity and accuracy of FIBS.

Jooda et al. [2] developed a feature-level fusion technique utilizing GSA that selects and merges the smallest pertinent meaningful texture attribute subsets from several occurrences of a fingerprint before the classification stage to determine whether the probing fingerprint is authentic or fake. The testing findings show that GSA is effective at decreasing the number of attributes while maintaining appealing efficiency, with a total RA of 97.31%. However, GSA can be enhanced by combining it with searching globally strategy, which increases feature fusion and speeds up FIBS identification.

According to these studies, an IBS with feature fusion achieves superior performance with a higher level of feature redundancy. This can be enhanced by utilizing an efficient optimization algorithm to choose attributes from the retrieved texture features of locally collected fingerprints. Improving the feature diversity of high-dimensional feature space has been given little attention in existing FS optimization algorithms. In this paper, a hybrid of ABC based on disruptive selection with GSA for optimal FS of extracted texture features to have an improved performance of FIBS was developed.

3. Materials and Methods

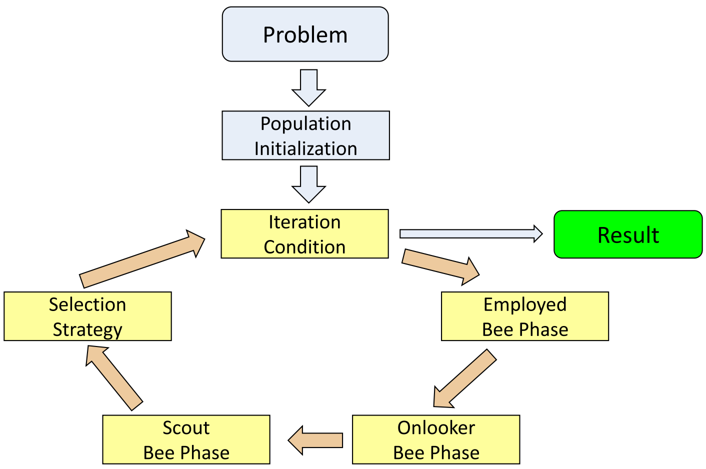
3.1. Materials

Biometric technology based on fingerprints is a pattern recognition device that confirms the authenticity of an individual fingerprint. The following phases were employed for FIBS training and testing: dataset acquisition, data preprocessing, feature extraction, FS, and classification. Figure 1 shows the fundamental flow diagram for the proposed system.

3.1.1. Dataset acquisition

The Dataset phase is the initial step in a vision device. During this phase, the multi-instance fingerprint biometric data repository was formed. Many of the datasets accessible online were

Figure 1
Model of the proposed methodology



taken in controlled situations, with photos focused on a specific computational goal. However, when data sets utilized by the algorithms change due to alterations in the circumstances in which the images were obtained, the efficacy of biometric equipment also changes [12]. This requires the database setup of a fingerprint repository that was acquired in an unregulated environment. Utilizing fingerprint images captured locally under an uncontrolled environment, a fingerprint database was set up. Multiple instances of fingerprints of one hundred and fifty (150) selected subjects were captured using a Futronic fingerprint scanner. The left and right hands of each subject were captured to set up the fingerprint database. A total of nine thousand (9000) gray scale images of one hundred and fifty (150) subjects were acquired to set up the fingerprint database. The Database contained six samples of the thumb, index, middle, ring, and pinky images of all the fingers. A repository of information including several instances of fingerprint images was used throughout the data collection step. The whole fingerprint image database was divided into two datasets: training and testing. The training dataset contains four images taken from each of the 134 captured subjects, totaling 5360 pictures. The dataset was tested using the best-quality instances that were collected from the left or right of the remaining two samples of each fingerprint instance of the 134 individuals and the sixteen (16) subjects who were not included in the training set.

3.1.2. Data preprocessing

The next phase is preprocessing, which is a series of image improvement techniques applied to the collected fingerprints to clarify the print pattern layout and pinpoint the print grids. Fingerprint RA is governed by fingerprint quality and the efficacy of the preprocessing technique. The fingerprint images in the two databases were preprocessed separately in order to enhance their characteristic. To ensure uniformity, the images were reduced to 100×100. To obtain the Region of Interest, images were cropped. The images' contrast and visual quality were then improved by histogram equalization.

3.1.3. Dataset texture feature extraction

A feature vector is a set of descriptive or quantifiable feature measurements that expresses the number of minutiae, singularities, points, and textural features. Texture attributes were extracted from the fingerprint's center point in this study, which acts as a basis for extraction of feature.

Texture attributes have been extracted from preprocessed images with Discrete Cosine Transform (DCT) to create global feature vectors. After extracting the texture attributes, the 100×100 pixel images were quartered to obtain four non-overlapping sub-images of size 8×8 pixels, and 2-D DCT was used on each sub-image to obtain a block of 8×8 DCT coefficients using Equation (1). The derived DCT coefficient matrices provide an efficient representation of the images in de-correlated pixels. The outputs of DCT were used as inputs to the FS phase.

3.2. Proposed methodology for ABCGSA

Feature fusion can be used in a multibiometric system to combine extracted characteristics from the same modality (intramodal) or from different modalities. Considering the size of the integrated feature set, feature-level integration suffers from the curse of dimensionality and could contain unnecessary or duplicate information. In addition, having a large number of feature sets raises the cost of storage and classification time [20]. The FS approach mitigates the effects of high dimensionality by identifying and eliminating irrelevant information. This serves to reduce the dimensionality of the input for the classification stage while simultaneously increasing the performance of the multibiometric system. Good classification performance was achieved by selecting and combining the most relevant and informative texture features extracted from the ten fingerprint images into a single feature vector to reduce the feature space by utilizing hybridized ABCGSA for FS.

In FIBS, a Back Propagation Neural Network (BPNN) was used in training and testing the optimized fused features gotten from the developed ABCGSA. The number of BPNN objects created was one hundred and fifty (150), which is the same to the number of subjects in the database. One hundred and thirty-four (134) BPNN objects were trained, and each object was trained per class. The BPNNs were trained using 5360 fingerprint samples.

The BPNN algorithm consists of one input layer, two hidden layers, and one output layer for error calculation and adjustment of weights of each neuron link. The response of the BPNN was dependent on weights, biases, and activation functions to achieve desired results. In this research, the weights are random values, which are equivalent to the number of input texture features of an individual; the biases used was set to 0.99, and the activation function used was tangent sigmoid (Tansig).

The verification process was implemented in order to evaluate the proposed system after the learning phase was completed. The fused feature sets were given as input to all BPNN objects during the verification process. The evaluation phase was done by testing the system with trained and untrained fingerprint images to calculate the percentage of accuracy and error. A set of one thousand eight hundred and twenty (1820) fingerprint samples was used to test the proposed system. The BPNN object that gave the maximum output value was identified to be the class of the test image.

3.3. ABCGSA development

The simple concept, use of few control parameters, easy implementation, and good exploration characteristics of ABC have made it frequently used in solving FS problems. ABC algorithm is also the best in terms of global search and self-improvement ability [20]. Research, however, has shown that ABC has poor exploitation characteristics with respect to solution search equation and difficulty in solving high-dimensional problems. This made ABC trapped in the local optimum, consequently affecting the feature diversity [21–24]. To compensate for the limitation of ABC, a hybrid of ABC based on disruptive selection with GSA, which can escape local minima to reach global optimal value and avoid loss of core information in the less fitted features, was developed to have an enhanced performance of FIBS. Improving the feature diversity of the optimization algorithm was considered by utilizing the developed algorithm on high-dimensional feature sets.

The ABC selection process was merged with GSA's FS update algorithms as shown in Algorithm 1. Initial parameters were established, and random initialization was utilized to produce a starting population inside the feature subset constraints using Equation (5). The weight vector for every generated feature was assessed utilizing the target function of generating an intramodal merged feature, which includes features that strongly correlate with one class but not with others, leading to the minimal error in classification possible.

During the employed bee phase, using Equations (11) and (12) in Section 4.1, each employed bee randomly selected a neighboring feature to modify the position of the feature. To choose the better feature among the new and old features, a greedy selection procedure was used. The location detail of the features was communicated to the onlooker bees in the dance region once all of the employed bees had completed the search operation.

At the Onlooker bee phase, Onlookers choose and update the solutions by changing the velocity and position of the onlooker bee using GSA using Equations (13)–(19) in Section 4.1. Onlooker bees use the disruptive selection strategy to determine the selection probability and improve population diversity while preventing early convergence. Onlooker bees then applied a local search mechanism of GSA on the highest probability feature in order to increase the exploitability of the basic ABC algorithm. The optimal feature was then returned to replace the feature with the low fitness value. Finally, scout bees determined which features had been abandoned and replaced them with new features using Equation (4) in Section 4.1.

3.3.1. Disruptive selection

For any random search algorithm, the exploration of the whole search space and exploitation of the near-optimal solution region can be balanced by retaining diversity in early and later iterations. It is critical to provide diversity to individuals in the initial population because diversity allows the algorithm to search the whole possible solution space. If the diversity is low, the method will most likely result in premature convergence, which is undesirable [1, 10, 25, 26]. Disruptive selection strategies can help to solve this problem by preserving population diversity. By modifying the definition of the fitness function, the disruptive selection method increases the probability of higher and lower individuals being picked.

Disruptive selection tends to preserve diversity somewhat longer because it favors both superior and inferior solutions. The definitions of selection probability and fitness function are defined in Equations 1, 2, and 3, respectively, and used in Equation (10).

$$p_i = \frac{fit_i}{\sum_{j=1}^{N} fit_j} \tag{1}$$

where fit_i is the fitness value of the i^{th} solution and p_i is the selection probability of the i^{th} solution. The fitness function is given by

$$f_i = \begin{cases} \frac{1}{f_i} f_i > 0 \\ |f_i|\, f_i \le 0 \end{cases} \tag{2}$$

$$fit_i = |f_i - \bar{f}_t| \tag{3}$$

where f_i is a specific objective function, f_t is the average of the objective values for the individuals in the population [1, 2].

3.4. System model

ABCGSA was developed by hybridizing ABC's selection mechanism with GSA's updating methods for FS. The major stages of the hybrid algorithm ABCGSA are given in the following:

Algorithm 1:

Step 1: Get extracted texture features
Step 2: Initialize the algorithm parameters Solution Number (SN), Maximum Cycle Number (MCN),
limit, G0, and α of ABCGSA
Step 3: Generate randomly distributed solutions to form the initial population by

$$D_{\mathrm{kd}} = L_d + r(U_d - L_d) \tag{4}$$

where 0 < r <1, Ud, and Ld are the upper and lower bounds for the dth dimension of the kth solution
Step 4: Evaluate fitness value using

$$y = D_{\mathrm{kd}} \tag{5}$$

$$F_k = \sum_{i=1}^{n} \sum_{k=z}^{n} (y_{i,k-1} - y_{i,k}) \tag{6}$$

$$w = \begin{cases} 1 & if\ w \le \overline{F_k} \\ otherwise\ w > \overline{F_k} \end{cases} \quad \text{where } w = F_k \tag{7}$$

$$if\ F_k > 0\ F_k = \frac{1}{F_k} \tag{8}$$

$$if\ F_k \le 0;\ F_k = F_k \vee \tag{9}$$

$$\mathrm{Fv}_k = F_k - \overline{F_k}_{\mathrm{avg}} \vee \tag{10}$$

where F_k, $\overline{F_k}_{\mathrm{avg}}$, and Fv_k are the objective function of each feature, the average of F_k of individuals in the population, and the fitness value of the k^{th} feature subset, respectively

1) Employed bee phase

Step 5: Employed bees update the current solutions using the ABC method

$$N_{kd} = D_{kd} + \varnothing_{kd}(D_{kd} - D_{rd}) \tag{11}$$

N_{kd} is the new solution in the neighborhood of D_k, and D_{rd} is a solution around D_{kd}
Step 6: calculate the selection probabilities of each N_{kd}

$$P_k = \frac{\mathrm{Fv}_k}{\sum_{n=1}^{\mathrm{SN}} \mathrm{Fv}_n} \tag{12}$$

2) Onlooker bee phase

Step 7: Onlooker bee phase Onlookers choose and update the solutions by changing the velocity and position of the onlooker bee using GSA

Calculate the masses $M_k(t)$, gravitational constant Z(t), total for $G_k^d(t)$, acceleration $a_k^d(t)$, velocity $V_k^d(t+1)$, and position $N_k^d(t+1)$ for every solution D_k

$$M_k(t) = \frac{\mathrm{FV}_k - \mathrm{WS}(t)}{\mathrm{BS}(t) - \mathrm{WS}(t)} \tag{13}$$

$$Z(t) = Z_0 \times \exp(-\beta \times \frac{\mathrm{iter}}{\mathrm{maxiter}} \tag{14}$$

$$G_k^d(t) = \sum_{j=1, j \ne i}^{\mathrm{kBest}} \mathrm{rand}_j G_{\mathrm{kj}}^d(t) \tag{15}$$

$$G_{\mathrm{kj}}(t) = Z(t) \frac{M_k(t) M_j(t)}{R_{\mathrm{kj}}(t) + \varepsilon} (D_j^d(t) - D_k^d(t)) \tag{16}$$

$$a_k^d(t) = \frac{G_k^d(t)}{M_k(t)} \tag{17}$$

$$V_k^d(t+1) = \text{rand}_k + V_k^d(t) + a_k^d(t) \tag{18}$$

$$N_k^d(t+1) = D_k^d(t) + V_k^d(t+1) \tag{19}$$

Step 8: Scout bee determines the abandoned solution and replace with a new solution using Equation (13)
Step 9: Output the best solution ever found
Step 10: Repeat from 17 to 19 until the stopping criterion is met

4. Experimentation, Results, and Analysis

4.1. Experimental setup

For the training and testing phases of FIBS, the following stages were used: dataset acquisition, data preprocessing, extraction of features, FS, and classification and performance evaluation using the developed ABCGSA. For simulating biometric authentication systems, the described algorithm was implemented in MATLAB version R16a using image processing and optimization toolboxes in the MATLAB development environment. A 2GHz processor, 128GB HDD (Hard Disk Drive), 4GB of RAM, and a 64-bit operating system on the Windows 7 platform are minimum requirements to run the algorithm.

4.2. Performance evaluation metrics

Evaluations were performed to assess the performance of the developed FS algorithm in selecting optimal features from the extracted texture feature space. The performance metrics employed in this research were sensitivity, FPR, FNR, RA, and RT. There was a significant shift in RA at these thresholds: 0.2, 0.35, 0.5, and 0.75; therefore, the metric results for ABC, GSA, and ABCGSA were analyzed using these thresholds. The tables and bar charts were used in presenting the results of the evaluation.

Sensitivity is known as the percentage of correctly detected positive cases. It's the percentage of relevant images that are correctly identified. The stability of the algorithms in response to changes in the training set is referred to as sensitivity. Sensitivity measures how well a classifier can identify positive labels. Sensitivity is calculated as defined in Equation (20).

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{20}$$

The ratio of correct classifications over the total number of samples is the RA. It's also referred to as the genuine positive rate. Developing algorithms of FS for classification with high classification accuracy and stability is still challenging [27, 28]. In classification techniques, the number of test records correctly or erroneously predicted by the model determines the number of predictions. Accuracy measures a classifier's overall efficacy and is computed as shown in Equation (21).

$$\text{RA} = \frac{TP + TN}{TP + FP + TN + FN} \tag{21}$$

The rate at which the system allows an unauthorized user as a valid user, allowing an impostor to have access to the system using Equation 22, is FPR.

$$\text{FPR} = \frac{FP}{TN + FP} \tag{22}$$

The rate at which the system assessed an authorized individual as an imposter user, that is, when the system refuses to grant a legitimate person access to the system using Equation 23, is FNR.

$$\text{FNR} = \frac{FN}{TP + FN} \tag{23}$$

where TP means true positive, indicating the number of images that have been accurately classified as correct.

FP stands for false positive, meaning the number of images incorrectly classified as correct when they're actually wrong.

TN means true negative, showing the number of images correctly classified as incorrect or out of classification and are indeed incorrect or out of classification.

FN stands for false negative, meaning the number of images wrongly classified as incorrect or out of categorization when they're actually correct [29–32].

The RT refers to how long it takes the system to identify an image that's been tested.

4.3. Results

Table 1 shows the comparison of FIBS results using ABCGSA, ABC, and GSA-based FS. Figures 2, 3, 4, 5, and 6 show the sensitivity, RA, FPR, FNR, and RT of the FIBS using the three FS algorithms.

4.4. Analysis

The results of FIBS for the developed ABCGSA at a threshold value of 0.75 show that the system had SEN of 99.03%, RA of 98.74%, FPR of 2.08%, FNR of 0.97%, and RT of 186 s, respectively. At a threshold value of 0.75, sensitivity improved by 1.34%, RA increased by 1.98%, FPR decreased by 3.75%, FNR decreased by 1.34%, and RT decreased by 30 s for ABCGSA-based FIBS compared to Jooda et al.'s [1] results. At these threshold values, sensitivity improved by 0.97%, RA improved by 1.43%, FPR decreased by 2.71%, FNR decreased by 1.01%, and RT increased by 119 s for ABCGSA-based FIBS compared to Jooda et al.'s [2] results. The results of FIBS for developed ABCGSA at a threshold value of 0.75 show that the system had RA improved by 8.74% when compared to Amirthalingam and Thangavel's [33] results.

The results evaluation showed that FIBS had higher sensitivity and RA when ABCGSA was used for FS compared to when standard ABC and GSA were used. This indicated that ABCGSA is more effective to discover global optimal features than other FS algorithms by reducing the feature space of important characteristics while attaining the best sensitivity and RA. This was due to the diversity caused by disruptive selection in populations to avoid premature convergence and being trapped in local optima. It was observed from the results that ABCGSA had minimal FPR and FNR compared to standard ABC and GSA. This implied that, when ABCGSA was used for FS prior to the BPNN classifier, the system had a minimal number of FPR and FNR because of a high value of sensitivity and therefore was able to recognize genuine fingerprints and exclude wrong fingerprints [10, 21–24]. Table 1 shows the comparison of ABCGSA, ABC, and GSA at a threshold value of 0.75. Table 1 shows that ABCGSA required

Table 1
Comparison of ABCGSA, ABC, and GSA

FS	SEN (%)	RA (%)	FPR (%)	FNR (%)	RT (s)
ABCGSA	99.03	98.74	2.08	0.97	186
ABC	97.69	96.76	5.83	2.31	216
GSA	98.06	97.31	4.79	1.98	305

Figure 2
Sensitivity of FIBS using ABCGSA, ABC, and GSA

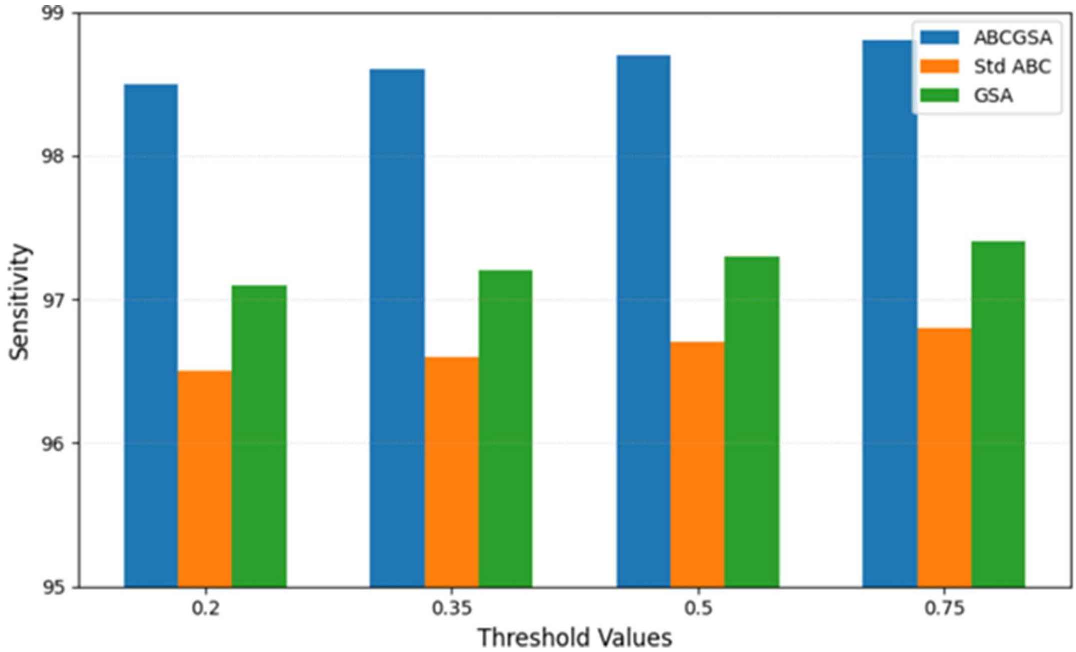


Figure 3
Recognition accuracy of FIBS using ABCGSA, ABC, and GSA

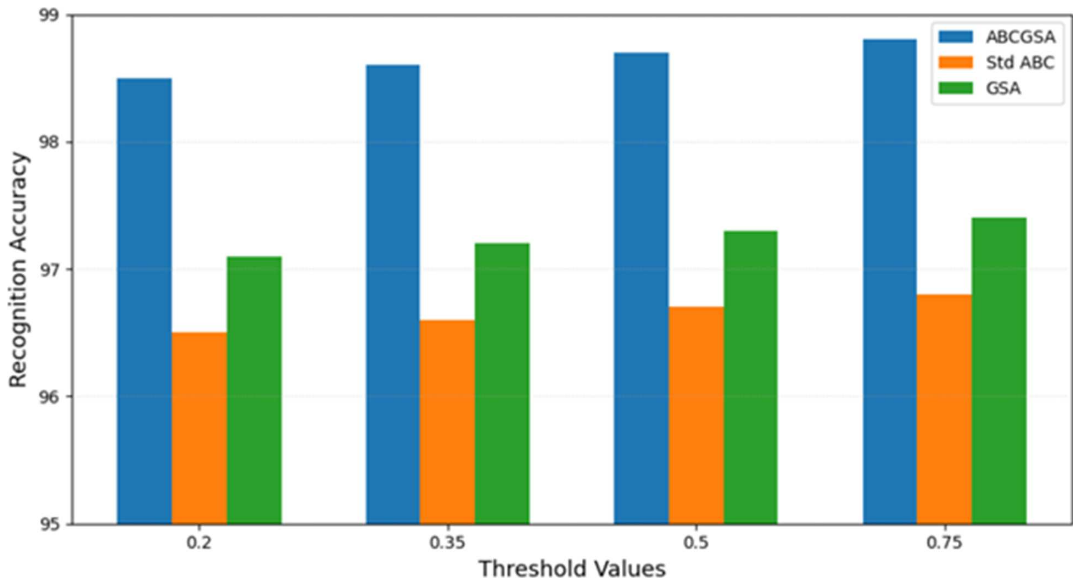


Figure 4
False positive rate of FIBS using ABCGSA, ABC, and GSA

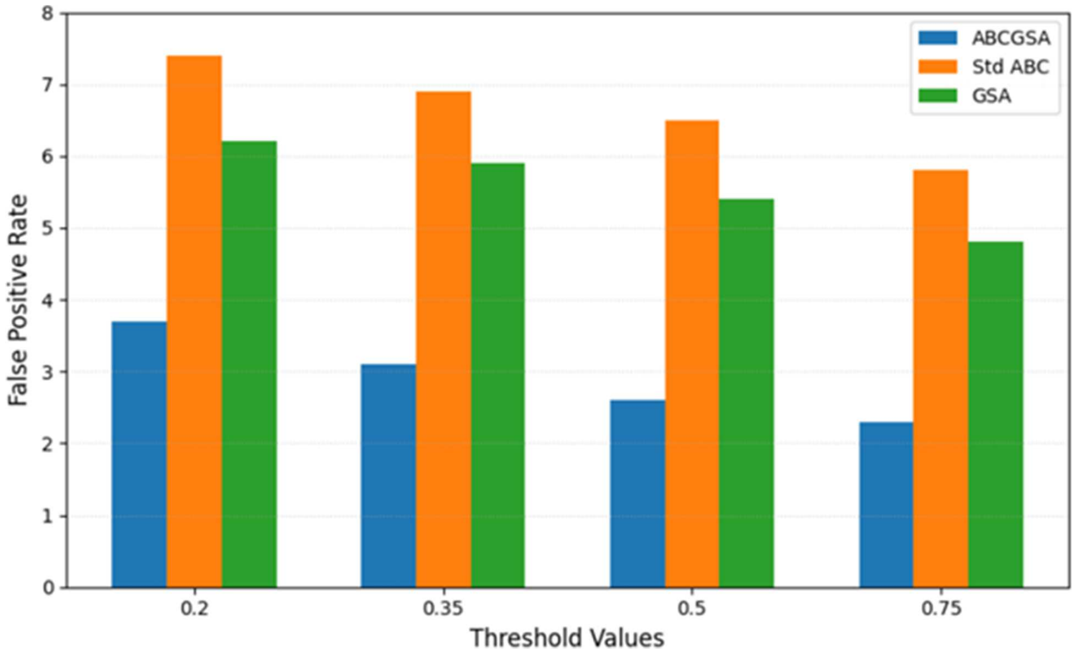
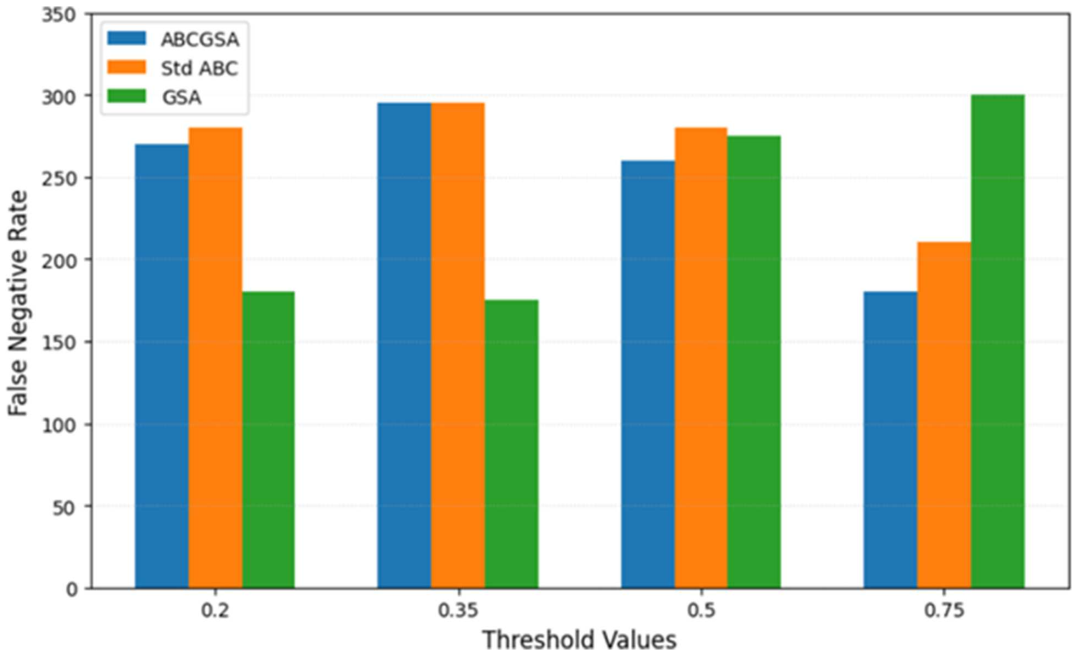


Figure 5
False negative rate of FIBS using ABCGSA, ABC, and GSA



the shortest execution time to produce the improved outcomes when compared to the individual algorithms utilized for ABC- and GSA-based FS. This meant that if ABC chose a feature subset, it was transferred to onlooker bees via disruptive selection-based GSA for further exploitation. The appropriate feature subsets are determined by the information supplied by onlooker bees. This helps FS to make the process of classification faster because the redundant and irrelevant features are removed from the feature set [16].

Figures 2–6 show the sensitivity, RA, FPR, FNR, and RT of the FIBS using the three FS algorithms. The figures show that the assessment results obtained by ABCGSA-based FS outperformed the individual algorithms. This proved the fact that hybridizing ABC and GSA for FS balances the exploration and exploitation levels of ABCGSA, which led to finding the most relevant features. In alignment with the reference by Chaudhary [16], the hybridized ABCGSA was more capable of avoiding the local optimal state and converging to the most beneficial features faster than ABC and GSA. This resulted in ABCGSA yielding higher sensitivity and RA with the lowest FPR and FNR that best categorize the features into the correct classes, and it has outperformed [26–28] related patterns observed in different datasets

Figure 6
Recognition time of FIBS using ABCGSA, ABC, and GSA

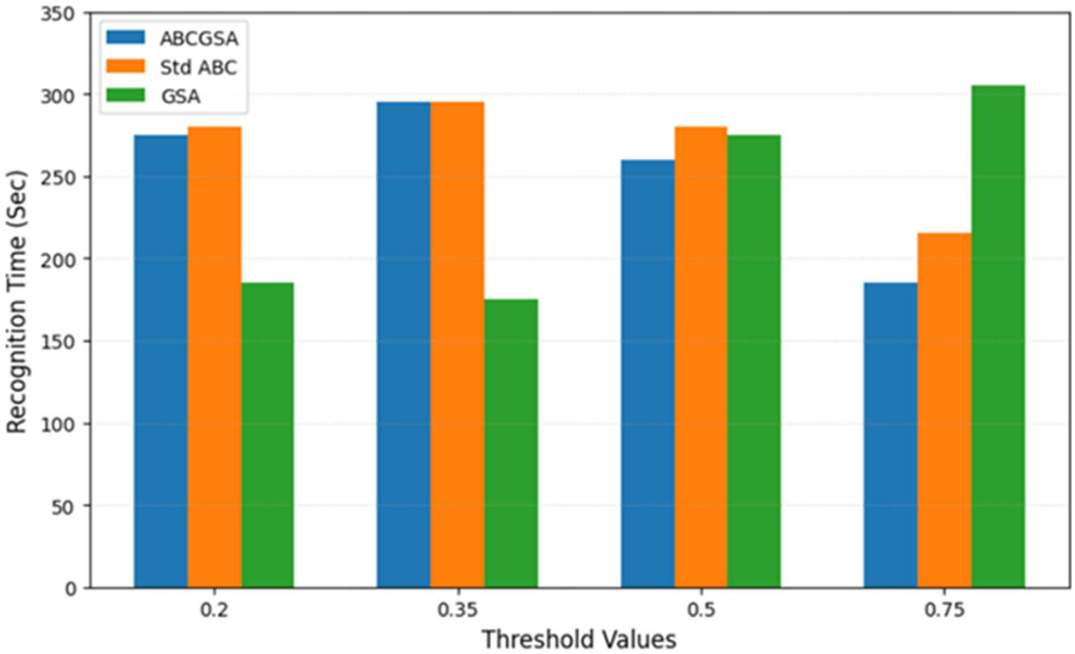


Table 2
State-of-the-art comparison of Hybridized ABCGSA for feature selection of biometric system

Refs.	FS model	ACC	FPR (%)	FNR (%)	RT (s)
[1]	ABC	96.76	5.83	2.31	216
[2]	GSA	97.31	4.79	1.98	305
[13]	MCSA	97.84	–	–	–
[11]	BA-ABC	92	–	–	–
[5]	Hybrid bio-inspired fuzzy	92.24	–	–	–
[17]	Step Gravitational Search Algorithm (SGSA), Support Tensor Train Machine (STTM)	70%	–	–	–
[37]	Hybrid ABC-PSO	90	0	10	–
Proposed FS	ABC-GSA	98.74	2.08	0.97	186

[29, 30]. It was observed that GSA, when compared with ABC, had a higher percentage of sensitivity and RA had lower FPR and FNR because of the exploitation ability of GSA to find the optimal features. While ABC had lower RT compared to GSA because of the exploration capability of ABC that led to its fast convergence rate. These results advanced the studies [34–36]. Table 2 presents the state-of-the art comparison of Hybridized ABCGSA for FS of a biometric system.

5. Conclusion and Future Scope

In this paper, hybridizing of the exploitation ability of GSA into the exploration capability of ABC based on disruptive selection was developed for optimal FS to reduce high-dimensional datasets' computational complexity to improves the performance of classification IBS. When compared with the existing algorithms used for FS, the results showed that ABCGSA's sensitivity and RA increased by 3.21% and 4.73%, while FPR and FNR decreased by 8.96% and 3.21%, and RT improved by 20 s, thus enhancing the efficacy of FIBS. Integrating textural characteristics from many occurrences of identical biometric traits utilizing an efficient F strategy considerably improves the performance of a biometric system. Random initialization of the population used in the developed ABCGSA can drive the solution pool away from optimal features, thereby affecting the convergence speed. The methodology was not tested on datasets in biometric fields such as face recognition, ear recognition, and palmprint recognition. The use of an initialization method that starts the ABCGSA optimization with a solution pool closer to optimal can be employed.

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Ethical Statement

The authors declare that this study did not require formal ethical approval because this study used secondary data that have been previously deanonymized to protect the privacy of the parties concerned.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/ruizgara/socofing.

Author Contribution Statement

Janet O. Jooda: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Sunday A. Ajagbe:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Misan Paul Etchie:** Software, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Oluyinka T. Adedeji:** Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Alice O. Oke:** Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Pragasen Mudali:** Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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