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Enhancing Accuracy and Efficiency of Iris Recognition Based on Variable Length Metaheuristic Approach

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Abstract

The rapid integration of digital technology into everyday life has significantly reshaped the developmental environment of adolescents. This paper investigates the psychological effects of digital overexposure on emotional development, drawing from a synthesis of secondary data and empirical research. Focusing on adolescents aged 14 to 18, the study analyzes how excessive and emotionally immersive use of digital platforms, particularly social media, influences self-esteem, depressive symptoms, emotional regulation, and gender-based responses.

The research reveals that emotional outcomes are not solely determined by the amount of screen time, but by the type of engagement and the user's emotional investment. Girls, in particular, demonstrate heightened vulnerability to emotional distress linked to digital behaviors, especially during periods of societal disruption like the COVID-19 pandemic. This study also integrates theoretical frameworks such as Social Cognitive Theory and the Socio-Technical Interaction Networks model to explain behavioral patterns and digital norms. Visual representations of data further illustrate key patterns in screen time and mental health, gender disparities, and pandemic-specific outcomes. The paper concludes with recommendations for educators, policymakers, and families to support healthy digital habits and outlines critical directions for future interdisciplinary and inclusive research. Ultimately, the goal is to inform the development of

responsive strategies that foster emotional well-being in the digital age.

Keywords: *Feature Selection, High-Dimensional Biometric Data, Iris Recognition, Variable Length Optimization, Meta-Heuristic*

Introduction

Modern security systems now depend on iris recognition technology as their most precise biometric solution since it surpasses different identification methods like fingerprints along with facial and vocal recognition [1], [2]. The human iris represents a tiny circular eye structure that develops complex unique patterns which stay unchanged from birth to death. Due to its distinguishable patterns, iris recognition represents an excellent security solution for demanding applications including border crossing operations and secure facilities along with national identity measures [3]. Recent research and development of iris recognition technologies advances because of rising needs from users for dependable biometric systems. The implementation of IRSs encounters specific obstacles that researchers need to resolve before achieving higher performance standards in real applications. Such issues as inadequate lighting, together with off-angle captures and partial occlusions, greatly affect the quality of iris images, as well as recognition system accuracy [4]. Processing high-resolution iris photographs with algorithms to extract suitable features represents a substantial difficulty for the development of fast and effective IRSs that operate efficiently on applications with many identity records. Iris recognition accuracy and computational efficiency depend heavily on selecting appropriate features as it is the main issue affecting these systems. The normalization procedure of iris images using different texture analysis approaches such as Gabor filters, Local Binary Patterns (LBP), and wavelet transform generates extensive dimensional feature spaces which result in many generated features [5]. The numerous input features often generate highly accurate identifications but introduce the curse of dimensionality that makes algorithm performance decline when features exceed training samples [6].

The issue often associated with high-dimensional features is that they generate a complex recognition procedure and introduce noise and redundancy that could negatively impact classifier performance. Efficient feature selection methods are crucial for identifying the most unique features by eliminating the system's redundant and noisy features. This method, through feature space dimensionality reduction, seeks to improve IRS performance without sacrificing operational efficiency. The large feature spaces of iris identification cause typical feature selection approaches to either perform poorly or require an excessive amount of processing power especially when operating with large datasets for real-time recognition. Research investigators employ meta-heuristic optimization algorithms to solve these obstacles because these algorithms effectively manage complicated high-dimensional optimization challenges in numerous domains [7]. The search capabilities of Meta-heuristic algorithms such as PSO, ACO, and Genetic Algorithms (GA) successfully explore large feature spaces to discover excellent or superior feature subsets [8]. Such programs draw their inspiration from natural phenomena while following evolutionary principles so they can traverse difficult solution settings while preventing themselves from getting stuck at near-optimal results. Meta-heuristic algorithms can solve the problems of standard feature selection approaches in iris recognition feature selection through their adaptable feature space search. Traditional meta-heuristic techniques operate with fixed-length representations that show limitations during the processing of iris data that contains mutable multidimensional features. Research into variable-length meta-heuristic algorithms led to the creation of VLPSO and VLBHO, along with possible advantages compared to fixed-length variants [9]. The methods enable adaptable changes to feature subset dimensions throughout optimization, thus improving both the exploration of feature space and the capability to solve iris identification problems.

The application of VLMA for iris identification feature selection stands primarily as a research subject. Research currently finds ineffective application of advanced optimization approaches to tackle problems that arise from IRSs. There is no adequate analysis available that compares different variable length meta-heuristic techniques when applied to iris feature selection. Therefore, this work aims to evaluate the performance of VLPSO and VLBHO, two variable-length meta-heuristic algorithms, as feature selectors in iris recognition. A variety of performance indicators, including accuracy, computing efficiency, and feature subset sizes, were used to evaluate the effectiveness of contemporary feature selection strategies with the conventional fixed-length methods utilizing benchmark iris datasets. The examination of the efficacy of these variable length meta-heuristic algorithms in iris recognition adds to the building of more accurate and efficient biometric systems; it also offers insights into the potential of these representations in optimization issues beyond iris detection, such as in machine learning and pattern recognition [10].

2. Literature Review

Many machine learning and pattern recognition tasks, such as iris identification systems, depend heavily on feature selection as a crucial preprocessing step. The enhancement of classification results and reduction of computational complexity requires efficient feature selection approaches especially during cases of high data dimensionality [10]. Feature selection problems have mostly been solved using metaheuristic optimization methods because these methods search large solution spaces efficiently for the optimal solution [11]. Most PSO-based and other metaheuristic computer techniques operate with fixed-length representations that might restrict their capacity to handle high-dimensional data, but recent development has brought about variable-length metaheuristic algorithms for feature selection that can solve this issue. For instance, Black hole optimization that performs variable-length searching within high-dimensional data has been used as a feature selection approach [12]. The optimization methodology allows changes in feature subset dimensions during the optimization process. Furthermore, Beheshti et. al [13] designed a fuzzy transfer function to let binary PSO perform variable-length searches during high-dimensional feature selection. Different metaheuristic optimization techniques form the basis of Ekinci et al.'s [14] research which predicts joint moments during sit-to-stand movements through biometric approaches. Their findings revealed the efficacy of metaheuristic feature selection in biomechanical applications. A study presented by [15], authors have suggested a hybrid firefly-PSO algorithm for feature selection and tested it on various datasets, including iris. Despite the importance of feature selection in IRSs, there has been little research into applying variable-length metaheuristics explicitly to this problem. The majority of contemporary iris identification algorithms rely on preset feature sets or simple feature ranking methods [12].

Iris data's high dimensionality and complicated feature interactions make it an excellent candidate for advanced feature selection algorithms. Another study presented by [16], authors have made an early step in this approach by developing a variable-length black hole optimization technique for feature encoding and selection in iris recognition; the presented approach performed better than the fixed-length methods. Additional research needs to be conducted on variable-length metaheuristics for iris feature selection because multiple explorations of optimization methods and hybrid solutions together with multi-objective formulations remain available. Variable-length metaheuristics have reportedly demonstrated potential in high-dimensional feature selection applications but require further investigation to be suitable for IRSs. The development of ideal variable-length feature selection algorithms adapted to iris data requirements presents itself as a necessary research pursuit for improving both the efficiency and performance of IRSs.

3. Background

3.1. Traditional Iris Recognition Techniques

Iris recognition has remained a reliable mode of biometric identification because of the distinctive features of the human iris. From image capture through segmentation, normalization, and feature extraction to matching phases, the traditional iris identification methods involve a number of crucial procedures [2]. Gabor filters and local binary patterns (LBP) are the most widely used feature extraction techniques available today. Research by Daugman [17] showed that Gabor filters serve as essential elements for iris feature extraction because they can collect both frequency and spatial data. The representation of the 2-D Gabor filter is given thus:

$$G(x,y;\varphi,\omega) = exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\sigma_a^2}+\frac{y'^2}{\sigma_b^2}\right]\right\} cos(2\pi\omega x'')$$

Where (x'',y'') are rotated coordinate φ is the orientation, ω is the frequency respectively, and σ_a, σ_b are scale parameters. Another common method, Local Binary Patterns (LBP), offers both computational efficiency and rotation invariance; the LBP operator can be defined as:

$$LBP_{N,r} = \sum_{n=0}^{N-1} h(g_p - g_c)2^n \text{ , } h(x) = \begin{cases} 1 & ,if\ x \geq 0 \\ 0 & ,otherwise \end{cases}$$

Where g_c represent the central pixels' gray value, g_p represent the gray values of N surrounding pixels in a circle of radius r, and h is the step function [5].

The combination of deep learning with traditional methods has recently been earmarked, with convolutional neural networks (CNNs) showing the greatest potential in both classification tasks and feature extraction for iris recognition [3].

3.2. Feature Selection Methods in Biometrics

IRSs heavily depend on feature selection methods because they diminish dimensionality while improving performance rates and streamlining computations. There are currently three types of feature selection methods - filter approaches, wrapper methods, and embedding methods [6], [18]. The evaluation of features using the filter methods relies on the inherent feature qualities rather than any specific classifiers; some examples of the filter methods are Information Gain, Correlation-based Feature Selection (CFS), and the Relief Algorithm. The computation speed of these methods remains high but they sometimes fail to deliver suitable subsets for specific classifiers. For the wrapper methods, the evaluation of feature subsets is performed using a predetermined classifier; the computation process of such methods takes more time but often yields optimal outputs for specific classification systems. Examples of the wrapper approach include RFE (Recursive Feature Elimination), SFS, and SBS. The adapted version of these strategies works best for classifiers used in the final system implementation. Embedded techniques unify model development steps with feature selection processes to obtain the advantages of the filter with wrapper strategies. The popular methods for embedded feature selection systems consist of LASSO together with Random Forest Feature Importance. Such procedures deliver satisfactory performance between computation speed and correct feature selection outcomes. Multiple iris recognition algorithms use combination features that demonstrate favorable outcomes [5]; these combined techniques merge different methods' most beneficial properties to resolve their particular weaknesses.

3.3. Meta-heuristic Algorithms for Feature Selection

Research interest has significantly increased in recent times regarding meta-heuristic algorithms because these algorithms can solve complex optimization problems, including the feature selection process in biometrics. Various algorithms draw their inspiration from natural events due to their ability to discover global search opportunities [7]. Numerous meta-heuristic algorithms have been used as feature selectors, such as GA, PSO, DE, ACO, and GWO. These different algorithms showcase their unique attributes while showing effective results when applied to various feature selection applications. The structure of a meta-heuristic algorithm for feature selection is as follows:

$$s^{k+1} = \mathrm{A}(s^k, q)$$

Where s^k is the current solution, s^{k+1} is the updated solution A is the update function; q represents the algorithm-specific parameters [8]. To handle high-dimensional datasets and shorten search times, new meta-heuristic algorithms have recently been designed with some enhancements. The efforts based on Variable Length Black Hole Optimisation (VLBHO) and Variable Length Particle Swarm Optimisation (VLPSO) [12] demonstrate the great promise of dynamic feature subset size adaptation in variable-length representations. The conventional fixed-size encoding is extended by these variable-length techniques to operate over dynamic search space dimensions.

$$\lambda^{k+1} = \begin{cases} \lambda^k + \Delta\lambda, & if\ rand < P_{mod} \\ \lambda^k - \Delta\lambda, & otherwise \end{cases}$$

Where λ^t represent the current length, $\Delta\lambda$ stands for the length change step, and P_{mod} is the length change probability [10].

This utilization of advanced meta-heuristics for optimization of the feature selection process in iris recognition indicates a significant breakthrough in their application to improve biometric systems' accuracy and efficiency, specifically in multi-dimensional feature spaces.

4. Methodology

In this section, the proposed VLBHO FS, VLPSO, and VLBHO PS are described along with the methods for problem formulation, feature extraction, data processing, and implementation. The process for evaluating competitive algorithms, iris recognition, feature selection, and adaptable metaheuristics is discussed.

4.1. Problem Formulation

The problem is formally formulated thus: the iris recognition features selection problem is described as VLMH algorithms. Assume a given iris image dataset as $D = \{(I_1, y_1), (I_2, y_2), \ldots, (I_N, y_N)\}$ with I_i representing the i-th iris image while the related class label is given as a variable. Consider that $F = \{f_1, f_2, \ldots, f_M\}$ is a set of the features extracted from the iris images, with M representing the overall feature number. The aim is then to determine which subset S ⊆ F would maximize the classification result; hence, the formulated feature selection problem is as follows:

$$\underset{T \subseteq F}{\text{minmize}}\ \Phi(T) = \beta\ Precision\ (T) + (1 - \beta).Correlation(T)$$

$$subject\ to\ |T| \leq \lambda_{max}$$

Where $\Phi(T)$ = fitness function,

Precision (T) = classification accuracy using S,

Correlation (T) = measure of the relevance or redundancy of the feature,

$\beta \in [0,1]$ = weighting factor,

λ_{max} = maximum allowed size of the feature subset.

A solution (particle or black hole) is represented in the variable length meta-heuristic algorithms context as a binary vector $x = (x_1, x_2, \ldots, x_M)$, where:

$$s_i = \begin{cases} 1 & ,if\ feature\ f_i is\ selected \\ 0 & ,otherwise \end{cases}$$

With the variable length, it implies the length of x can be dynamically changed during the process of optimization, with $1 \leq |x| \leq M$. The velocity update rule for VLPSO is given as:

$$u_i^{k+1} = \omega \cdot u_i^k + \alpha_1 \rho_1 (p\_best_i - s_i^k) + \alpha_2 \rho_2 (gbest - s_i^k)$$

Where ω = inertia weight,

α_1 & α_2 = acceleration coefficients,

ρ_1 & ρ_2 = random numbers [0,1],

p_best_i and g_best_i = personal best and global best positions, respectively.

The position update rule for VLBHO is given as:

$$s_i^{k+1} = s_i^k + random\ (s_H - s_i^k)$$

Where s_H the black holes' position (optimal),

random = a random number [0, 1].

Figure 1 portrays the major components of a VLMH technique for feature selection in iris identification. The first phase of the process is obtaining the raw iris image data, followed by the feature extraction step to provide a set of original features. Then, these features are fed into the VLMH algorithm, which is the central component of the system (shown in the figure as "VL-Meta-Heuristic"). The suggested technique uses variable-length operators to evolve sets of possible features to dynamically explore the feature space. Each candidate subset's fitness over feature set size and classification accuracy is evaluated using a fitness function. A subset of the best features with discriminative power is generated by the iterative optimization process, which keeps improving the feature selection. The final classification stage uses the chosen optimal feature subset to make predictions for iris recognition. This figure offers helpful details regarding the seamless incorporation of VLMH into the pipeline for iris recognition. It also highlights the fact that these sophisticated techniques can increase the recognition accuracy and feature set selection efficiency. Flexibility in navigating the intricate feature landscape inherent in iris identification problems is made possible by the optimization step's dynamic feature subset size adjustment; the number of dimensions searched over can be altered on the fly thanks to Variable Length. This is possible as the lengths and positions of this solution are iteratively updated by the optimization process until a stopping requirement is satisfied, such as a pre-set number of iterations.

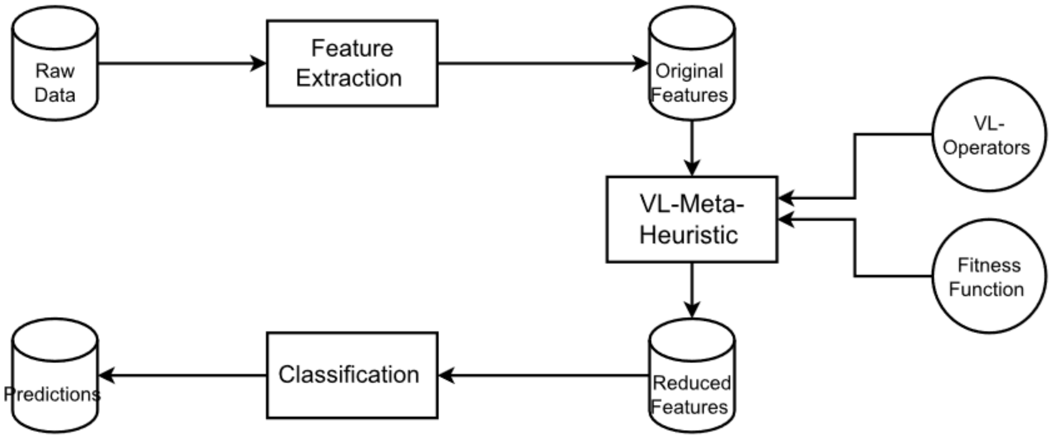

Figure 1 Workflow of VLMH feature selection for iris recognition.

4.2. Variable Length Optimization Algorithms

VLBHO and VL PSO, in contrast to existing approaches, suggested employing a vector of variable length to carry out feature selection throughout high-dimensional space. The two algorithms' primary structures are similar, but their updating processes and some specific implementations differ.

Algorithm 1. Main algorithm of variable-length optimization

```
Require: Dataset-D, maximum iterations IterMax, population size PopNum
Ensure: Selected feature subset
1: Initialize population with variable length solutions
2: Evaluate fitness of all solutions
3: for iter = 1 to IterMax do
4.    Update solutions using VLBHO or VLPSO mechanism
5.    Evaluate fitness of updated solutions
6.    Update global best solution
7.    if No improvement for k iterations, then
8.       Execute length modification procedure
9.    end if
10: end for
11: Return: Best feature subset identified
```

Algorithm 1 displays the primary components of the VLBHO and VLPSO; the inputs to the algorithms are dataset D, PopSize (the population size), and MaxIter (the maximum number of iterations). The first step is the generation of a range of variable-length solutions (see line 1), each of which is a possible subset of features. These solutions are checked for fitness (see line 2) using a performance metric. Lines 3–10 comprise the main optimization loop, which executes for MaxIter. The VLBHO or VLPSO approaches are used to update the solutions in each iteration (line 4), and the improved solutions are then assessed for fitness (line 5). The best-found feature subset is taken as the global best (see line 6). If, after a predetermined number of rounds, no significant improvement is noted, a length-changing mechanism is initiated to prevent stagnation (lines 7-9). This enables the program to explore several search space dimensions. Algorithm 2 explains how to update the VLBHO solution. The method generates a velocity vi(d) for each dimension d of a solution xi based on the difference between the black hole xBH and the present solution.

$$v_{i(d)} = rand() \times \left(x_{(BH)(d)} - x_{i(d)}\right)$$

A transfer function T (mostly an S-shaped function) is then applied to this velocity (line 3):

Example of Iris image

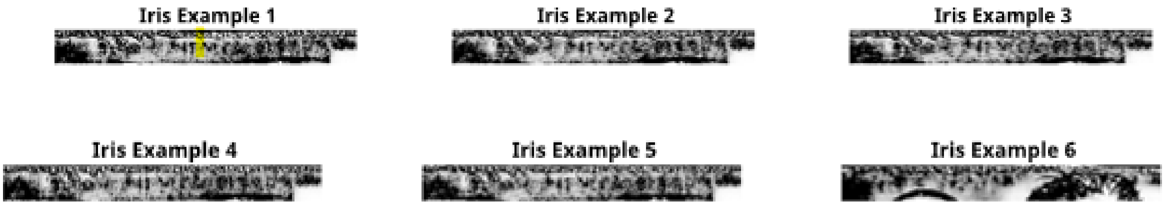

Figure 2. Examples of iris images after segmentation and normalization

Algorithm 2. The update solution of VLBHO algorithm

Require: Current solution si, black hole sH
Ensure: Updated solution
1: for each dimension j do
2. ui(j) = random() ×(sH(j) −si(j))
3. Γ =TransferFunction(ui(j)) ▷ S-shaped or V-shaped function
4. if random() < Γ then
5. si(j) = 1 −si(j) ▷ Invert binary value
6. end if
7: end for
8: return Updated si

$$S-shaped(x) = \frac{1}{1 + e^{-\gamma x}}$$

Or a V-shaped function:

$$V-shaped(x) = |tanh(\delta x)|$$

Where γ, δ represent constants.

The probabilistic decision to flip the dimension's binary value is then based on the output of this transfer function (lines 4-6). The procedure for updating the VLPSO solution is explained in Algorithm 3. Although it employs the usual PSO velocity update equation (line 2), it has a structure similar to VLBHO.

$$v_i(d) = w \times v_i(d) + c_1 \times rand() \times (p_i(d) - x_i(d)) + c_2 \times rand() \times (g(d) - x_i(d))$$

where w = inertia weight,

c_1 & c_2 = acceleration coefficients,

pi and g = personal best and global best solutions, respectively.

Lastly, the length-changing process that both VLBHO and VLPSO employ is described in Algorithm 4; this process modifies the solution's length according to the performance of various population divisions. Line 1 indicates the division with the highest average fitness, while the new maximum length for that division is established in line 2. Next, the remaining divisions (lines 3–11) are appropriately downsized, either by removing extra dimensions or adding new ones.

Algorithm 3. The update solution of VLPSO algorithm

Require: Current solution s_i, velocity u_i, personal best p_i, global best g
Ensure: Updated solution and velocity
1. for each dimension j do
2. $ui(j) = \omega \times ui(j) + a1 \times random() \times (pi(j) - si(j)) + a2 \times random() \times (g(j) - si(j))$
3. $\Gamma = TransferFunction(ui(j))$ ▷ S-shaped or V-shaped function
4. if $random() < \Gamma$ then
5. $s_i(j) = 1 - si(j)$ ▷ Invert binary value
6. end if
7: end for
8: return Updated s_i and u_i

Algorithm 4. The key procedure of length changing

Require: Current population, number of segments SegNum
Ensure: Updated population with adjusted lengths
1. OptimalSeg ⟵ Segment with highest mean fitness
2. NewMaxLen ⟵ Length of solutions in OptimalSeg
3. for each segment seg= OptimalSeg do
4. $AdjustedLen \leftarrow NewMaxLen \times seg/SegNum$
5. if $Current\ length < AdjustedLen$ then
6. Extend with randomly initialized dimensions
7. else
8. Truncate to appropriate length
9. end if
10. Recalculate fitness of modified solutions
11. end for
12. return Updated population

These techniques enable efficient high-dimensional feature space exploration using VLBHO and VLPSO by dynamically altering the solution lengths. The length-varying mechanism and variable length representation help overcome the limitations of fixed-length approaches in FS tasks, enabling more effective search space exploration. 12

4.3. Dataset and Evaluation

The popular CASIA-IrisV4 Dataset was utilized for the evaluation of the efficiency of the VLBHO approach in iris recognition systems; this dataset is an updated version of the CASIA-IrisV3 and it is made up of 6 subsets, three of which are from the CASIA-IrisV3 dataset (CASIA-Iris-Lamp, CASIA-Iris-Twins, and CASIA-Iris-Interval). Three more subsets (CASIA-Iris-Distance, CASIA-Iris-Thousand, and CASIA-Iris-Syn) were further added to the dataset. Generally, the CASIA-IrisV4 is comprised of 54,607 iris images from 1,000 virtual participants and more than 1,800 real subjects. Each iris image is an 8-bit gray-level JPEG file that was either synthesized or captured in near-infrared light.

5. Results and Analysis

This comparative analysis of the proposed VLMH for iris recognition is presented in this section; the analysis was based on the Cumulative Match Characteristic (CMC) curves and confusion matrices of the three evaluated algorithms.

4.1. Experimental Setup

The purpose of this study is to evaluate metaheuristic techniques using variable lengths. In this study, VLPSO and VLBHO were the two primary methodologies upon which our study's algorithms were based.

4.2. Dataset and Feature Extraction

The investigations were conducted using the conventional iris image databases. The popular Gabor filters are effective in capturing texture information in iris images. Furthermore, the VLBHO optimization technique generates high-dimensional feature vectors, which complicate feature selection and dimensionality reduction.

4.3. Implements the Algorithms

In this work, the two VLBHO variants that were implemented are VLBHO with Partial Search (VLBHO-PS) and VLBHO with Full Search (VLBHO-FS). The goal of each implemented algorithm was to choose the optimal feature subsets from the Gabor features; these techniques were compared to the VLPSO algorithm.

4.4. Experimental Setup

Tests using MATLAB R2021b Iris recognition were performed using the selected features, and a Random Forest classifier with 100 trees was employed. Training and testing subsets (80 % and 20 % respectively) were created, and up to 20 iris classes were taken into account in the experiment to enable a thorough multi-class assessment of the algorithms' performance.

4.4.1. Performance Metrics and Visualization

The performance of the proposed methods was thoroughly analyzed using the following performance evaluation metrics:

Confusion Matrices: The classification performance of each method across all classes was visualized by creating the confusion metrics for each method [19], [20].

CMC curves: The CMC was plotted for each method to compare the rank-based performance of all methods in recognition tasks [21].

Average Performance Metrics: This metric offers a general comparison between the proposed VLBHO & VLPSO methods.

4.4. Results Analysis

Figure 3 displays a CM of the VLBHO FS approach applied to an iris detection task with Gabor features. The matrix displays the performance over 20 distinct iris classes, with actual classes on the y-axis and predicted ones on the x-axis. A high percentage of accurate classifications is indicated by the yellow squares along the diagonal, which showcases the predicted class and the actual class match. There are a few incorrect classifications, as evidenced by the off-diagonal regions' preponderance of dark blue. This illustration shows that the VLBHO FS algorithm achieves high classification accuracy across most iris classes when combined with Gabor features. Misclassifications are visible in this confusion matrix, especially for classes 11 and 17 as shown by the yellow squares off the diagonal (class confusion). Results indicate that the VLBHO FS Gabor method successfully differentiates between different classes of iris with only a few misclassifications as seen from the confusion matrix (CM).

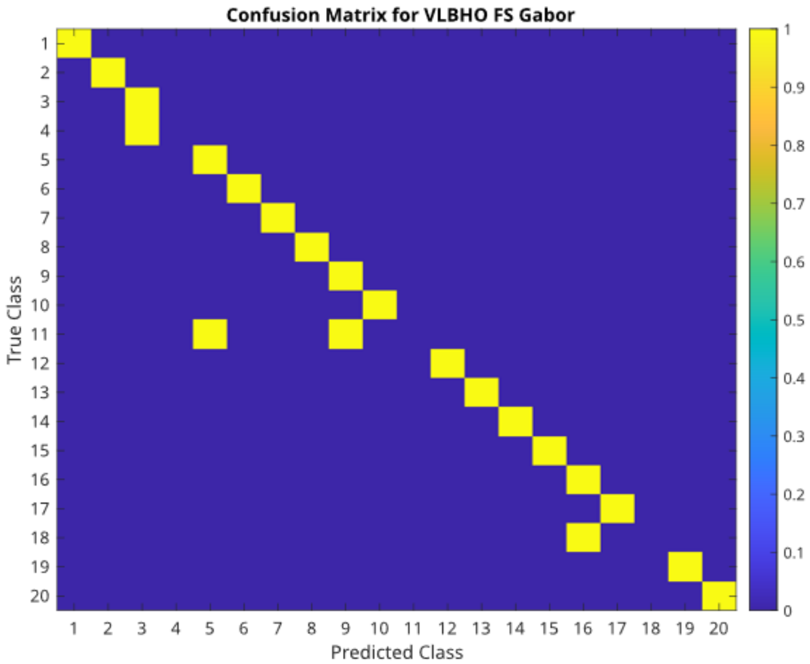

Figure 3 Visual representation of the CM for the VLBHO FS Gabor across 20 classes

Figure 4 displays the CM for the VLBHO PS for iris identification across 20 classes. The confusion matrix is a helpful tool in classification problems. While the darker blue off-diagonal regions show few misclassifications, the light blue diagonal squares show accurate classifications. This matrix, in contrast to the VLBHO FS approach, primarily represents variable performance. Given the existence of the light blue squares that substantially departed from the main diagonal, there are clear instances of misclassifications for classes 6, 7, 8, and 9. Class 10 showed a bright yellow square that suggests a good number of accurate classifications. The VLBHO PS Gabor method, in comparison to the VLBHO FS approach, shows higher error rates and lower consistency across classes, indicating that the PS strategy may be less successful in this situation. In summary, the method provides a respectable level of accuracy in iris classification.

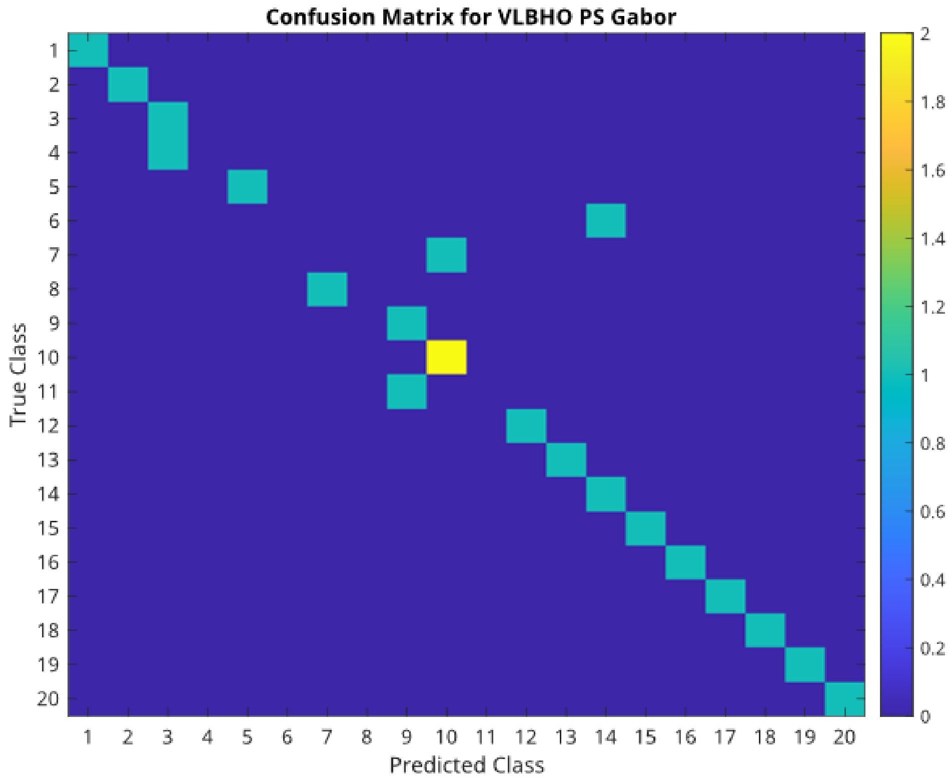

Figure 4 CM for VLBHO PS Gabor across 20 iris classes.

A CM that assesses the effectiveness of the VLPSO method using Gabor features for iris recognition across 20 classes is shown in Figure 5. The diagonal of the light blue squares indicates accurate classifications, and it performs well in the majority of classes. The off-diagonal areas, which are mostly dark blue, indicate a low overall rate of misclassifications. Class 10 exhibits extraordinarily high accuracy, as indicated by the bright yellow square that is displayed. Interestingly, misclassifications are visible, especially for classes 19 and 20, which are denoted by light blue squares that are orientated away from the main diagonal. This suggests that these classifications were occasionally mistaken for one another. The VLPSO Gabor approach exhibits strong stability in classification accuracy across the majority of classes, with few instances of severe errors. This method demonstrates effective performance in differentiating various iris classes, exhibiting improvements over the VLBHO PS method in certain aspects, while still allowing for further refinement in the accurate classification of the final classes.

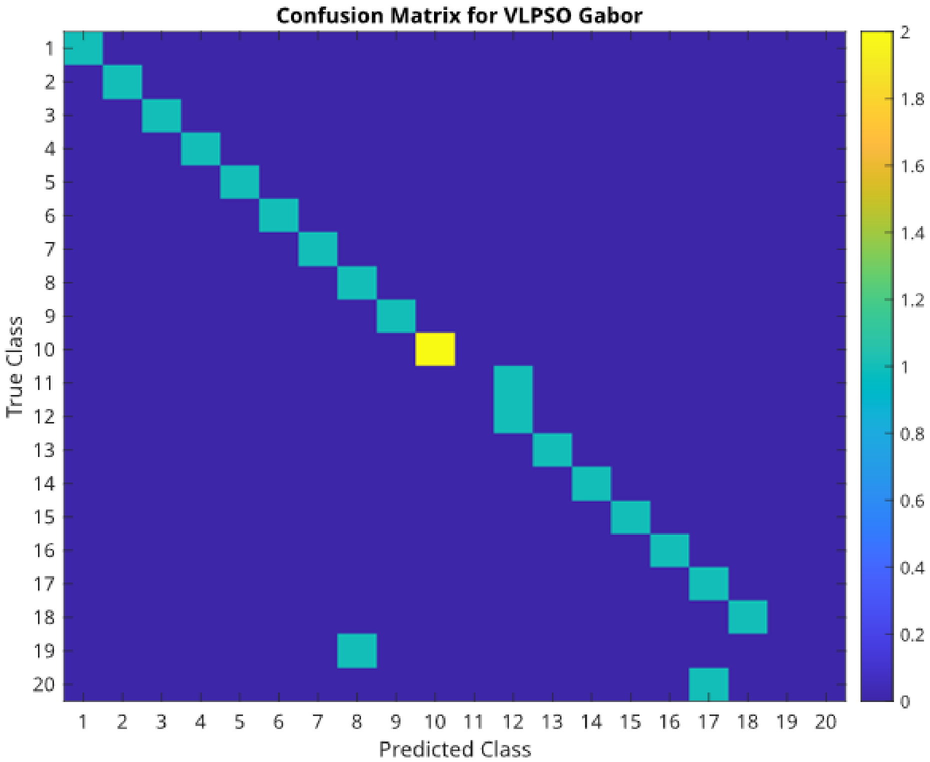

Figure 5 CM for VLPSO Gabor across 20 distinct iris classes

Figure 6 displays the CMC curves for the proposed iris recognition methods; the CMC curve shows how rank (x-axis) and recognition rate (y-axis) are correlated, demonstrating how performance becomes better as more top matches are taken into account. The three methods show improving iris recognition rates with ascending ranks and reaching 100% at elevated ranks. VLBHO PS Gabor (red line) is overall better, particularly at lower ranks, as it goes up faster than the others. VLBHO FS Gabor (blue line) and VLPSO Gabor (yellow line) are similar, with several crossover points where one is better than the other at different ranks. Hence, the three methods are almost perfect at rank 18 and are considered accurate. This allows us to compare the three methods in the iris recognition task, considering both their immediate recognition and their ability to get correct matches in the top ranks.

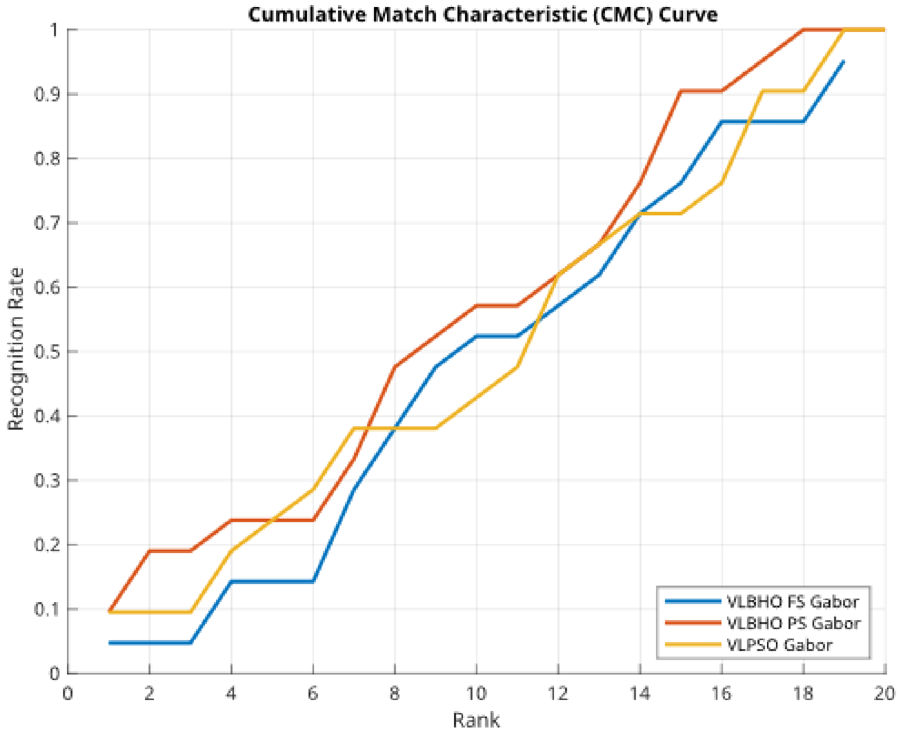

Figure 6 CMC curves of the performance of the three algorithms using Gabor features for iris recognition

The experiments demonstrate the effectiveness of variable length metaheuristic algorithms for IRS feature selection. On all 20 iris classes, the VLBHO FS, VLBHO PS, and VLPSO with Gabor features exhibit good performance. Every approach has a different confusion matrix, but for the majority of the classes, VLBHO FS routinely delivers excellent performances and has great accuracy. This means that the full search strategy although computationally expensive provides good feature selection. VLBHO PS performs well in some classes (class 10 in particular) but overall is more inconsistent. The trade-off between computational efficiency and accuracy needs to be examined further, especially in large-scale applications where processing time is key. Between the two VLBHO variants, VLPSO does well in the majority of classes but has difficulty in the final few. This indicates that there is greater potential for optimization, whether through parameter adjustment or hybrid strategies that draw on the advantages of several techniques. The CMC curves give a full picture of the algorithm's performance, and at higher ranks, all three methods are very similar. VLBHO PS is better at lower ranks which is good for applications that need quick but approximate matches. This result shows that algorithm selection is a function of the intended application; VLBHO FS is the best for high-security systems where precision is critical; VLBHO PS is best for systems that need fast processing time, with a gradual decline in accuracy is acceptable. The advantages of this variable-length technique are demonstrated by the implementation using the feature space of iris images. Compared to fixed-length approaches, these techniques can capture more subtle iris textural patterns due to the dynamic variation in feature subset lengths, which improves recognition rates. Subsequent investigations should explore alternative iris databases, examine the impact of different image quality categories on algorithm performance, and develop hybrid methodologies that integrate distinct metaheuristic strategies. Figure 7 shows the comparison of the performances of the VLPSO algorithm with Gabor features across 20 iris classes. While Figure 8 shows the Performance of VLBHO PS with Gabor features on iris classification task using various metrics. Moreover, Figure 9 illustrates the Performance of VLBHO PS with Gabor features on iris classification task using various metrics.

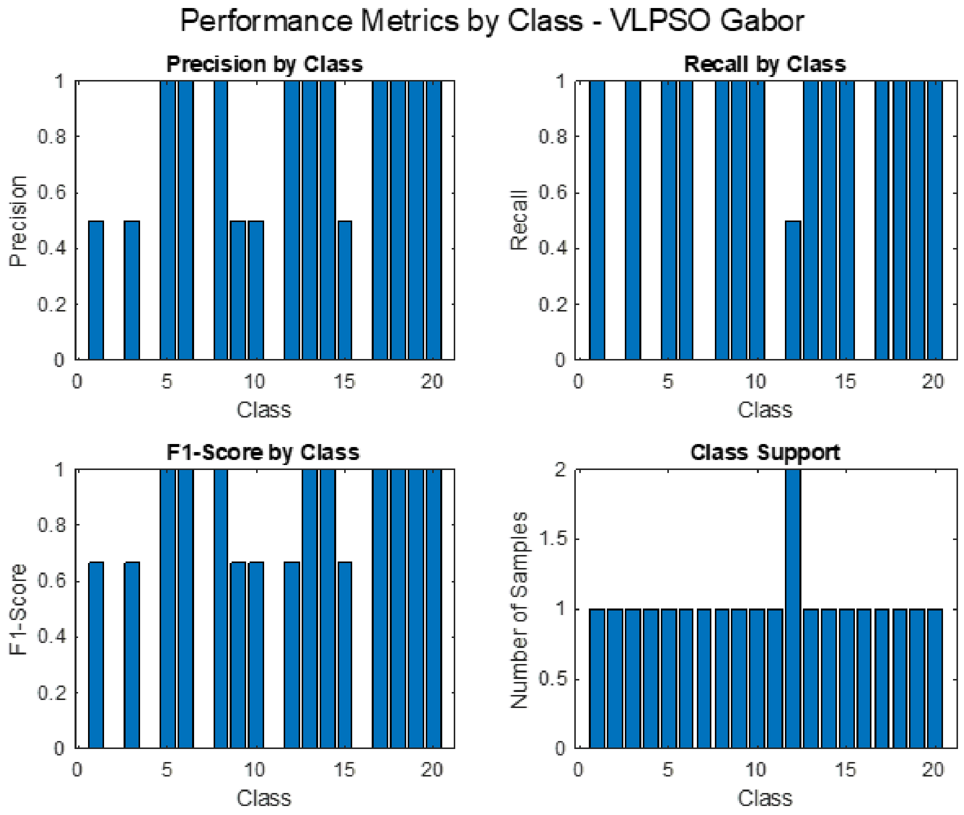

Figure 7 Comparison of the performances of the VLPSO algorithm with Gabor features across 20 iris classes.

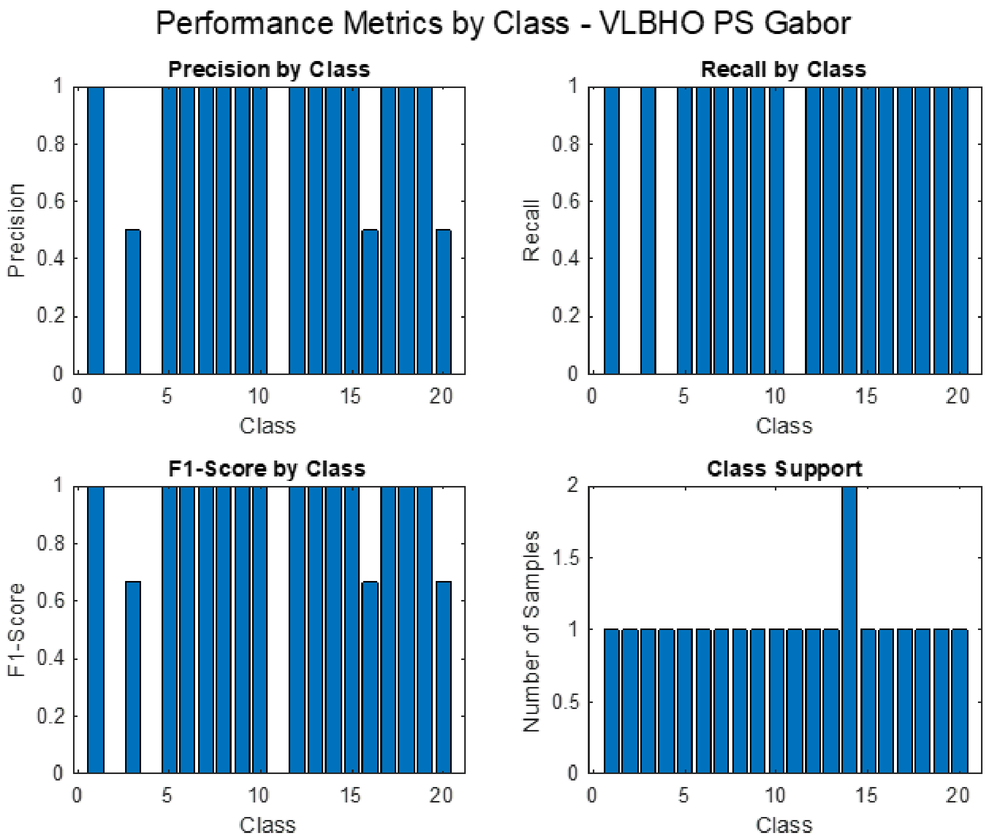

Figure 8 Performance of VLBHO PS with Gabor features on iris classification task using various metrics

Figure 9 Performance of VLBHO PS with Gabor features on iris classification task using various metrics.

As seen in the VLPSO implementation in Figure 8, there are variations in the performance of the various classes, with the recall and precision for classes 5-7, 13-15, & 18-20 being significantly notable. This supports the finding that VLPSO strikes a compromise between computational effectiveness and precision. Recall is very stable throughout most classes, based on the performance pattern, but precision varies significantly, especially in classes 8–12, indicating difficulties in reducing false positives for these particular iris patterns. When compared to VLPSO, the VLBHO PS produced a more consistent performance profile in terms of recall metrics (Figure 9), which confirms the conclusion that VLBHO PS demonstrates both respectable accuracy and computational efficiency. The algorithm's resistance to changes in class distribution is demonstrated by the rather stable F1 scores across most classes; however, the class support distribution peaks at class 13, suggesting a probable data imbalance that may impact the learning patterns of the algorithm.

Although there is some variation in the precision measures, particularly in classes 15–17, the general pattern indicates better reliability compared to VLPSO & VLBHO PS. The idea that VLBHO FS performs the best across classes, while having a greater computational cost, is supported by Figure 4,7, which demonstrates that the VLBHO FS performance measures achieved the most reliable pattern across the three techniques on the recall and F1-score metrics. The approach demonstrated its dependability for high-security applications where consistent accuracy is essential despite the modest imbalance in the class support distribution in the initial classes.

5. **Conclusion**

This study introduces and tests three algorithms for feature selection in eye recognition using Gabor features. The algorithms are called VLBHO FS, VLBHO PS, and VLPSO, and they can handle varying lengths of data. The study shows that these ways can make IRSs more accurate and efficient. Final Thoughts Our results show that all three ways work well, each having its advantages. VLBHO FS is designed to provide a good mix of accuracy and computing resources. It works well for different tasks and is great for applications that require high accuracy. DLTH VLBHO PS is more reliable, but it tends to do better at the lower end of scores, which creates chances for short matches. Results may differ for each person, but the VLPSO method is fair and works well for most types, even if it's not perfect for all iris types. The results show that the variable-length feature selection method is effective for working with complicated and high-dimensional iris images. These algorithms change the size of feature subsets as needed, allowing them to better handle the dense patterns in iris surfaces and possibly work better than fixed-length methods. This study also highlights areas for further research and possible improvements. The gaps in VLBHO PS and the difficulties VLPSO has with certain classes indicate possible ways to improve the algorithms. The iris database used, the limited use of only one method for extracting features (Gabor filters), and the complicated set of features could be some limits that future research might improve.

References

1. Y. Yin, S. He, R. Zhang, H. Chang, and J. Zhang, "Deep learning for iris recognition: a review," *Neural Comput. Appl.*, pp. 1–49, 2025.

2. M. Trokielewicz, A. Czajka, and P. Maciejewicz, "Iris recognition after death," *IEEE Trans. Inf. Forensics Secur.*, vol. 14, no. 6, pp. 1501–1514, 2018.

3. M. Wang and W. Deng, "Deep face recognition: A survey," *Neurocomputing*, vol. 429, pp. 215–244, 2021.

4. Z. Zhao and A. Kumar, "Towards more accurate iris recognition using deeply learned spatially corresponding features," in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 3809–3818.

5. R. Gad *et al.*, "Iris recognition using multi-algorithmic approaches for cognitive internet of things (CIoT) framework," *Futur. Gener. Comput. Syst.*, vol. 89, pp. 178–191, 2018.

6. J. Miao and L. Niu, "A survey on feature selection," *Procedia Comput. Sci.*, vol. 91, pp. 919–926, 2016.

7. M. Abdel-Basset, R. Mohamed, O. M. Elkomy, and M. Abouhawwash, "Recent metaheuristic algorithms with genetic operators for high-dimensional knapsack instances: A comparative study," *Comput. Ind. Eng.*, vol. 166, p. 107974, 2022.

8. A. Kumar, M. Nadeem, and H. Banka, "Nature inspired optimization algorithms: a comprehensive overview," *Evol. Syst.*, vol. 14, no. 1, pp. 141–156, 2023.

9. T. O. Q. Saraf, N. Fuad, and N. S. A. M. Taujuddin, "Framework of meta-heuristic variable length searching for feature selection in high-dimensional data," *Computers*, vol. 12, no. 1, p. 7, 2022.

10. T. Butler-Yeoman, B. Xue, and M. Zhang, "Particle swarm optimisation for feature selection: A hybrid filter-wrapper approach," in *2015 IEEE congress on evolutionary computation (CEC)*, IEEE, 2015, pp. 2428–2435.

11. J. M. Saarwade *et al.*, "A novel approach for iris recognition system using genetic algorithm," *J. Artif. Intell. Technol.*, vol. 4, no. 1, pp. 9–17, 2024.

12. T. O. Q. Saraf, N. Fuad, and N. S. A. M. Taujuddin, "Feature encoding and selection for Iris recognition based on variable length black hole optimization," *Computers*, vol. 11, no. 9, p. 140, 2022.

13. Z. Beheshti, "A fuzzy transfer function based on the behavior of meta-heuristic algorithm and its application for high-dimensional feature selection problems," *Knowledge-Based Syst.*, vol. 284, p. 111191, 2024.

14. E. Ekinci, Z. Garip, and K. Serbest, "Meta-heuristic optimization algorithms based feature selection for joint moment prediction of sit-to-stand movement using machine learning algorithms," *Comput. Biol. Med.*, vol. 178, p. 108812, 2024.

15. Asraa, Safaa Ahmed, et al. "An Accurate Model for Text Document Classification Using Machine Learning Techniques." *Ingenierie des Systemes d'Information* 30.4 (2025): 913.

16. S. Jayachitra, M. Balasubramani, A. M. Kaleem, J. Karthik, G. Keerthiga, and R. Mythili, "An efficient ranking based binary salp swarm optimization for feature selection in high dimensional datasets," *Meas. Sensors*, vol. 35, p. 101291, 2024.

17. J. Daugman, "How iris recognition works," in *The essential guide to image processing*, Elsevier, 2009, pp. 715–739.

18. A. M. Nor, S. Halunga, and O. Fratu, "Neural network based IRSs-UEs association and IRSs optimal placement in multi IRSs aided wireless system," *Sensors*, vol. 22, no. 14, p. 5216, 2022.

19. Z. S. Naser, H. N. Khalid, A. S. Ahmed, M. S. Taha, and M. M. Hashim, "Artificial Neural Network-Based Fingerprint Classification and Recognition.," *Rev. d'Intelligence Artif.*, vol. 37, no. 1, 2023.

20. N. K. Jabbar, M. Naderan, and M. S. Taha, "HybridIoMT: A Dual-Phase Machine Learning Framework for Robust Cybersecurity in Internet of Medical Things.," *Int. J. Intell. Eng. Syst.*, vol. 18, no. 4, 2025.

21. N. S. Ali, A. F. Alsafo, H. D. Ali, and M. S. Taha, “An Effective Face Detection and Recognition Model Based on Improved YOLO v3 and VGG 16 Networks,” *J. homepage http//iieta. org/journals/ijcmem*, vol. 12, no. 2, pp. 107–119, 2024.