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The Effect of Meta-heuristic Methods on the Performance of Image Classification

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Abstract

Classification accuracy is strongly affected by the quality of the input features. In recent years, datasets have increased in size and number of features. Analysis of huge datasets can be challenging due to redundant, noisy, and irrelevant features that may reduce the classifier's performance. Feature selection is a vital process in which the best subset of features from the original dataset is chosen. The feature selection strategy is critical for increasing classification accuracy while decreasing computational costs. This research proposed a method for classifying lip print images by exploiting meta-heuristic methods and optimization-based feature selection methods. It involves four main phases: pre-processing, feature extraction, feature selection, and classification. After pre-processing, the features are extracted from the enhanced image. Meta-heuristic methods such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Water Cycle Algorithm (WCA) are studied for feature selection using the mean function as the objective function. Finally, the lip print images are classified using a support vector machine (SVM). In this research, the experimental results are compared in terms of accuracy, error, sensitivity, and precision rate between three meta-heuristic methods and the accuracy rate of the proposed method with other algorithms that do not use meta-heuristic methods. The accuracy reached 97.9%, 96.8%, and 95% using WCA, PSO, and GA, respectively.

Keywords: Classification; Feature selection; Genetic Algorithm; Particle Swarm Optimization; Water Cycle Algorithm.

تأثير طرق الاستدلال الفائقة على أداء تصنيف الصور

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دقة تصنيف الصور تتأثر بجودة الصورة والميزات التي تحتويها الصورة. في السنوات الأخيرة ، زاد الاهتمام في تصنيف الصور مع كمية البيانات الهائلة من حيث الحجم وعدد الميزات داخل الصورة. وبذلك يكون تحليل البيانات الضخمة أمرًا صعبًا بسبب الميزات الزائدة عن الحاجة والميزات التي ليس لها علاقة بالصورة التي قد تقلل من أداء التصنيف. يعد اختيار الميزة خطوة مهمة تهدف إلى تحديد أفضل مجموعة فرعية من الميزات من مجموعة البيانات الأصلية. وتعد طريقة اختيار الميزات ضرورية لتحسين دقة التصنيف وتقليل تعقيد النموذج. اقترح هذا البحث طريقة لتصنيف صور بصمات الشفاه من خلال استغلال طرق الاستدلال الفائق لاختيار الميزات المهمة لتحسين الاداء. يتضمن البحث أربع مراحل رئيسية: المعالجة الأولية للصورة ، استخراج الميزات ، اختيار الميزات ، والخطوة الاخيرة تصنيف الصور. بعد المعالجة الأولية ، يتم استخراج الميزات من الصورة المحسنة. تتم دراسة طرق الاستدلال الفائق مثل الخوارزمية الجينية (GA) ، وتحسين سرب الجسيمات (PSO) ، وخوارزمية دورة حياة الماء (WCA) لاختيار افضل الميزات باستعمال المتوسط الحسابي كوظيفة موضوعية. أخيرًا ، يتم تصنيف صور طباعة الشفاه باستعمال آلة المتجهات الداعمة (SVM) في هذا البحث تمت مقارنة النتائج التجريبية من حيث الدقة والخطأ والحساسية ومعدل الدقة بين ثلاث طرق للاستدلال الفائق ومقارنة دقة الطريقة المقترحة مع الخوارزميات الأخرى التي لا تستعمل طرق الاستدلال الفائق. وصلت الطريقة المقترحة الى دقة عالية وكانت النتائج كالتالي 97.9% و 96.8% و 95% باستعمال WCA و PSO و GA على التوالي.

1. Introduction

Image classification performance can be reduced by dimensionality, redundancy, noise, or irrelevant features. Machine learning algorithms, which use feature selection (FS), reduce memory usage and computational time by eliminating redundant features. FS methods are divided into two main categories. The first is filtering techniques, which are based on specific attributes. The second is the wrapper technique to evaluate specific features using machine learning. Wrapper methods are computationally expensive, even though they are more accurate than filter methods. Minimizing the size of selected features speeds up classification performance and reduces computational time [1].

There are many types of population-based meta-heuristic algorithms, such as (a) swarm intelligence algorithms (SI), which mimic the social behavior of insects and animals. (b) Evolutionary algorithms (EA) are based on natural evolutionary processes. (c) Physical and chemical principles inspire natural phenomenon algorithms (NP). Meta-heuristic algorithms have been used as FSs, such as Genetic Algorithms (GAs) [2], Ant Colony Algorithm [3], Particle Swarm Optimization (PSO) [4], [5], Artificial Bee Colony (ABC), Salp Swarm Algorithm (SSA) [1], Grey Wolf Optimizer (GWO) [6], Harmony Search (HS) [7], Seagull Optimization Algorithm (SOA) [8], and Water Cycle Algorithm (WCA) [9], [10], etc. In this paper, WCA, PSO, and GA are used to find the optimal global solution to improve the performance of a person identification algorithm using a lip print dataset.

The proposed method consists of four phases. The first phase is pre-processing the dataset. In the second phase, the feature extraction (FE) of lip prints is extracted using the diagonal line operator, Sobel operator, Canny operator, and Hough transform (HT); these two phases are described in detail in [11]. The third phase is FS using the WCA, PSO, and GA. Finally, the classification was performed using SVM. This paper is organized as follows: Section 2 presents related works. The background of the meta-heuristic methods used is presented in Section 3. In Section 4, we present the datasets. In Section 5, the proposed method is described. Results and discussions are presented in Section 6. Finally, conclusions and future works are presented in Section 7.

2. Related Works

Meta-heuristics methods have recently demonstrated excellent performance in dynamic and global search optimizations [12]; the methods have been widely applied in a variety of fields [13], including global optimization [14], image processing [15], and cloud computing scheduling [16].

According to the literature, meta-heuristic methods such as evolution-based, swarm-based, physics-based, and human-based methods are employed as FS. Meta-heuristic approaches balance exploration and exploitation phases to avoid convergence or being stuck in local optima [17], [18]. It is possible to use meta-heuristics alone or in combination with other methods to select features, and both ways provide better results than traditional methods.

Firstly, algorithms used single meta-heuristics methods, such as Zhang et al. [19], which suggested a binary backtracking approach for feature selection. The goal of this research is to detect the symptoms of leukemia malignancy. Dhal et al. [20] proposed a stochastic fractal search technique for optimal identification. Compared to other conventional approaches, this algorithm attained a high level of accuracy. Tiwari [21] applied the Cuckoo Search algorithm (CS) to face recognition. Face recognition proved efficient with its ability to find the most matching image. Sgârciu and Enache [22] implemented the Binary Bat Algorithm (BBA) to classify NSL-KDD datasets. Sharma et al. [23] modified GWO to identify symptoms of Parkinson's disease by selecting sub-features. Ibrahim et al. [24] applied SSA as a feature selection (SSA-FS). SSA-FS was evaluated on medical breast, bladder, and colon cancer datasets. Jabbar and Zainudin [25] used WCA to reduce attributes in rough set theory. WCA performed better than other methods for selecting optimal attributes.

Secondly, hybrid algorithms combine two or more meta-heuristic methods, such as Parham and Mozghan [26], who presented a hybrid FS approach based on PSOs for local search. To pick the feature subset, HPSO-LS is integrated into PSO. Mistry et al. [27] used PSO-GAs-based feature selection algorithms to identify facial emotions. Ke et al. [28] developed PSO and spiral-shaped these mechanisms to find the best features. Majdi et al. [29] proposed an algorithm combining GA and the Grasshopper Optimization System (GOA) to create a binary hybrid algorithm. GOA uses grasshopper foraging and swarming behavior to create its algorithm. Rahul and Harjot [30] proposed a hybrid composition of SOA and Antlion Optimization (ALO). Half of the population was updated using SOA, while the other half was updated using ALO. The position update equations were also modified with many random factors to increase population variation. Bhattacharyya and Chatterjee [31] proposed combining an HS with the Mayfly Algorithm (MA). The HS further develops this method after finding solutions in different search regions.

3. Backgrounds

In this section, we present the meta-heuristic methods used in this paper.

3.1 Genetic Algorithm

GAs are generally designed using Darwinian concepts and natural evolutionary processes to identify the optimal answer from a population of candidate solutions. The three underlying GA operators are selection, crossover, and mutation [32]. A random set of solutions, usually represented in binary form, is chosen when GA is run. Each solution is assigned an objective function based on its fitness. Three operators are applied for each generation, and the population of solutions is modified until the criterion is satisfied. More specifically, GA exploits a random

search to solve an optimization problem. Table 1 provides the initialization parameters used for GA. Algorithm 1 shows the steps of GA to select optimal features after extracting features.

Table 1: GA Parameters.

Parameters	Value
No. of Generation	500
Population size(Pop – size)	20
Probability of Crossover(PC)	0.7
Probability of Mutation(PM)	0.01

Algorithm 1: FS of GA for lip print images

Input: The FE set of the original image; **Output:** A reduced set of features

Begin

- 1: Create a random population according to (Pop-size).
- 2: Apply an objective function to the population.
- 3: If the stopping condition is not met, continue.
- 4: Choose the best individuals and repeat the process to produce the solutions.
- 5: Apply crossover and mutation operation for the selected individuals.
- 6: Evaluate the fitness of new individuals using the mean function.
- 7: Change the worst individual with less error.
- 8: Return the best FS.

End

3.2 Particle Swarm Optimization

Eberhart et al. introduced PSO, a population-based meta-heuristic method [33]. The PSO is based on the behavior of birds and fish. In many empirical studies, the PSO has proven to be efficient. Each particle in PSO has a position (P) and velocity (V). Initially, the (P) and (V) of the particles are initialized randomly. In each iteration, the particles update (P) by updating their (V) for the global and personal best solution. The (P) and (V) of each particle are updated as in Eqs. (1) and (2).

$$V_i^{t+1} = w^t + C_1 R_1^t (pBest_i^t - p_i^t) + C_2 R_2^t (gBest^t - p_i^t) \quad (1)$$

$$p_i^{t+1} = p_i^t + V_i^{t+1} \quad (2)$$

Where (W) is the inertia coefficient, C_1 & C_2 are the personal and global learning coefficient, $pBest$ & $gBest$ are the best positions obtained.

Table 2 provides the initialization parameters used for PSO. Algorithm 2 shows the steps of PSO to select optimal features after extracting features.

Table 2: PSO Parameters.

Parameters	Value
No. of Generation	500
Swarm Size(S – Size)	20
(W)	0.7
pBest & gBest	2

Algorithm 2: FS of PSO for lip print images**Input:** The FE set of the original image; **Output:** A reduced set of features**Begin****1:** Initialize the (P), and (V) of the particle randomly.**2:** Estimate the particles using an objective function.**3:** If the stopping condition is not met, continue.**4:** Compute (gBest) & (pBest) based on the fitness value obtained from (step 2)**5:** Calculate the (V) for each particle and update the (P) using Equations (1) & (2).**6:** Return the best FS.**End****3.3 Water Cycle Algorithm**

The method was introduced by Eskandar et al. [34]. The WCA consists of four primary components: generating the initial population, simulating the flow of streams into rivers or oceans, modeling evaporation conditions, and replicating the rainfall process. The first step in WCA involves creating an initial population to represent a matrix of streams. Equation (3) is randomly generated, and thus the matrix is given as follows: population size (N_{pop}) and number of variables in the design (D), respectively:

$$Total\ population = \begin{bmatrix} Sea \\ River_1 \\ River_2 \\ River_3 \\ \vdots \\ StreamN_{sr+1} \\ StreamN_{sr+2} \\ StreamN_{sr+3} \\ \vdots \\ StreamN_{pop} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & x_3^1 & \dots & x_D^1 \\ x_1^2 & x_2^2 & x_3^2 & \dots & x_D^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{N_{pop}} & x_2^{N_{pop}} & x_3^{N_{pop}} & \dots & x_D^{N_{pop}} \end{bmatrix} \quad (3)$$

The first step is to create (N_{pop}) streams. Then, the sea and rivers are chosen among several of the best individuals in N_{sr} , the rest of the population is added together, and the remainder follows the streams into rivers or directly into the sea.

In N_{sr} is the summation of the rest of the population (N_{Stream}) as streams flow into the rivers or flow directly into the sea, and each river absorbs water from streams are calculated using the following Eq. (4):

$$NS_n = round \left\{ \left| \frac{Cost_n - Cost_{N_{sr+1}}}{\sum_{n=1}^{N_{sr}} C_n} \right| \times N_{Streams} \right\}, \quad n = \{1, 2, 3, \dots, N_{sr}\} \quad (4)$$

Where NS_n is the number of streams flowing into specific rivers and the sea.

Equations (5), (6), and (7) suggest new locations for streams and rivers in the WCA exploitation phase:

$$\vec{X}_{Stream}(t+1) = \vec{X}_{Stream}(t) + rand \times C \times (\vec{X}_{Sea}(t) - \vec{X}_{Stream}(t)) \quad (5)$$

$$\vec{X}_{Stream}(t+1) = \vec{X}_{Stream}(t) + rand \times C \times (\vec{X}_{River}(t) - \vec{X}_{Stream}(t)) \quad (6)$$

$$\vec{X}_{River}(t+1) = \vec{X}_{River}(t) + rand \times C \times (\vec{X}_{Sea}(t) - \vec{X}_{River}(t)), \quad (7)$$

Where t is an iteration index, $1 < C < 2$, the best value for C equal 2, and the $rand =$ uniformly distributed random number $[0,1]$.

A stream provides a better solution than a river; thus, the two places are switched as part of PSO's behavior to locate the ideal spots (i.e., the river turns into a stream, and the stream turns into a river). The sea and a river can be swapped.

The evaporation method was developed to prevent the optimal local solution [9]. Whether the river or stream is close enough to the ocean for evaporation must be determined. According to Eq. (8), the following standard for evaporation between a river and the sea is used:

$$if \|\vec{X}_{Sea}^t - \vec{X}_{River j}^t\| < d_{max} \text{ Or } rand < 0.1 \quad j = 1,2,3, \dots, N_{Sr} - 1 \quad (8)$$

Perform training process by uniform random search,

End

Where d_{max} is a tiny number close to zero, the raining method is used after evaporation, and new streams are created at various locations (such as a mutation in the GA). Table 3 provides the initialization parameters used for WCA. Algorithm 3 shows the steps of WCA to select optimal features after extracting features.

Table 3: WCA Parameters.

Parameters	Value
No. of Generation	500
Population size(Pop – size) (Number of rains drops)	20
Nsr (Number of rivers)	80
dmax	$1e - 3$

Algorithm 3: FS of WCA for lip print images

Input: The FE set of the original image; **Output:** A reduced set of features

Begin

1: Choose the initial parameters.

2: Create the initial $Pop - size =$ size of an image randomly.

3: Evaluate the cost of each stream by using the maximizing objective function.

4: Determine the initial population's rivers, streams, and (the best solution = sea).

5: Determine River and Sea flow intensity using Eq. (4) // NSn is the No. of streams, $Cost = O.F$, $NStreams =$ the rest of the population, $Nsr =$ the No. of the best individuals.

6: Calculate the new locations for streams and rivers utilizing the following Equations (5), (6), and (7).

7: Check the evaporation condition to avoid local optima, as shown in Equation (8).

8: When the evaporation condition is met in (step 7), the rain will occur, and streams will be formed in different places // such as a mutation in the GAs.

9: Check the stopping conditions.

10: Return the best FS.

End

4. Datasets

In this paper, the proposed method is tested using the dataset of lip prints, which consists of 148 lip print images, and the two websites that provide images of lip prints [35] and [36]. Table 4 provides details about the datasets. An example image of a lip print can be seen in Figure 1.

Table 4:The details about datasets.

Datasets	Datasets details	No. of lip prints
[35]	There are 15 individuals, each with four lip print images, with no indication of gender.	60
[36]	There are 22 individuals, each with four lip print images, with 9 males and 13 females.	88
Total		148

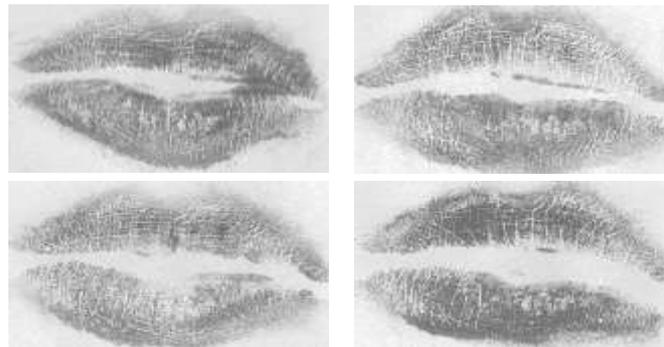


Figure1: lip print dataset example.

5. Proposed Method

The proposed method consists of four phases, as follows:

5.1 Pre-processing: The steps of the first phase are, briefly, the following:

- Convert test images to grayscale and select the *lower middle (LM)* part of all lip prints. The selected area was (65x80) pixels for an image $a(x, y)$. Figure 2 shows the lip topography.
- A thresholding process separates the background from the object, followed by a Gaussian operator to smooth lip prints. Figure 3 illustrates the steps involved in the pre-processing phase of the original image.

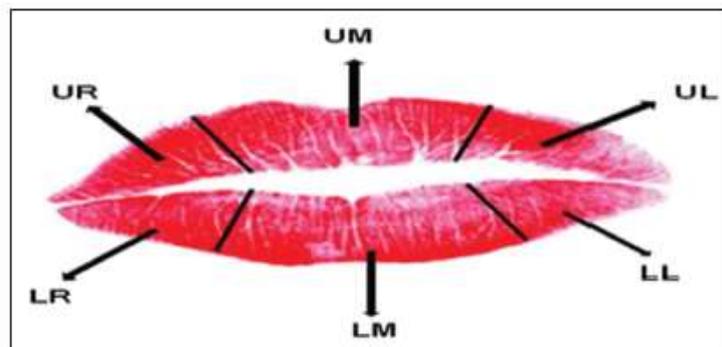


Figure 2: Lip topography is divided into six parts. The upper right(UR), upper middle(UM), upper left(UL), lower left(LL), lower middle(LM), and lower right(LR)

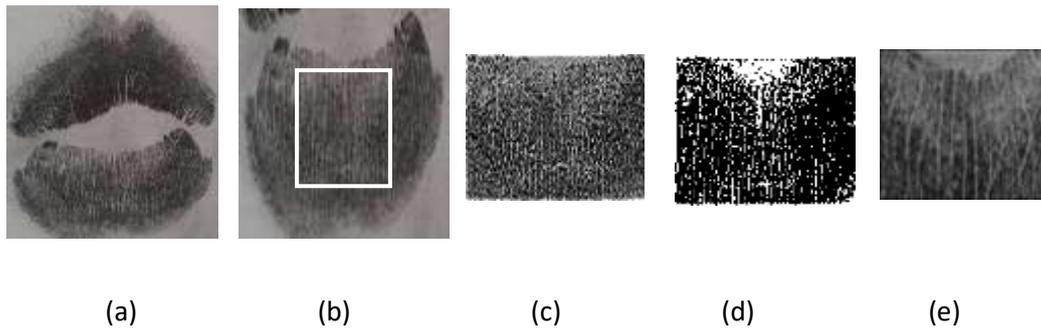
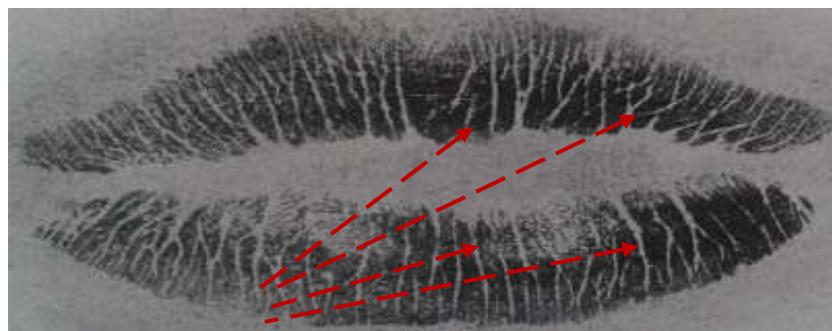


Figure-3 The pre-processing stage. (a) the original lip print, (b) the grayscale of the lip print and selection of the (LM), (c) the LM of the lip print, (d) the lip print thresholding, and (e) the lip print with a Gaussian filter applied.

5.2 Features Extraction: In the second phase, lips are covered with irregular furrows (reticular depressions) forming lines, as shown in Figure 4. Each person's lips have a unique pattern feature extracted by the following steps:

- Furrows are detected by the ± 45 diagonal and vertical Sobel operators; the operators' matrices are shown in Figure 5. Follow that by applying the Canny Operators to the lip print using Eq. (9). The steps in Algorithm 4 show how to combine lip print features into a single image.
- The next step is to detect vertical straight lines using the *Hough Transform (HT)*. Figure 6 shows the feature extraction phase. These phases are described in detail in [11].



Lip Furrows

Figure 4: An illustration of the simple example furrows on the lips.

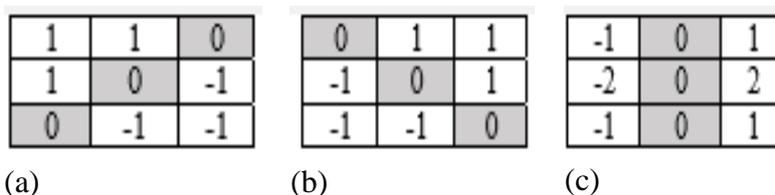


Figure 5: The operator's matrices (a) diagonal line $+ 45$, (b) diagonal line -45 , and (c) vertical Sobel operator

$$Icom(x, y) = \{d1[a(x, y)] \cup d2[a(x, y) \cup VS[a(x, y)]\} \tag{9}$$

Where: $Icom(x, y)$ is the image, which combined the FE, $a(x, y)$ the interesting region in lip print after applying pre-processing phase, $d1 a(x, y)$ diagonal lines + 45, $d2 a(x, y)$ diagonal lines - 45, and $VS a(x, y)$ is the extracted vertical lines using Sobel operator.

Algorithm 4: Creating an image using three lip prints

Input: Determine $a(x, y)$ // exciting region of the lip after applying pre-processing stage on it.

Output: $Icom(x, y)$ // combine all features in a single image.

Begin

1: For $j=1$ to the number of lips for a person

2: Apply +45 diagonal lines on $a(x, y)$; see Figure 6(a) // $d1[a(x, y)]$

3: Apply -45 diagonal lines on $a(x, y)$; see Figure 6(b) // $d2[a(x, y)]$

4: Apply the Vertical Sobel operator on $a(x, y)$; see Figure 6(c) // $VS[a(x, y)]$

5: Collect the results of Steps 2,3 and 4 to generate $Icom(x, y)$; see Figure 6(d) // by Eq. (9).

End

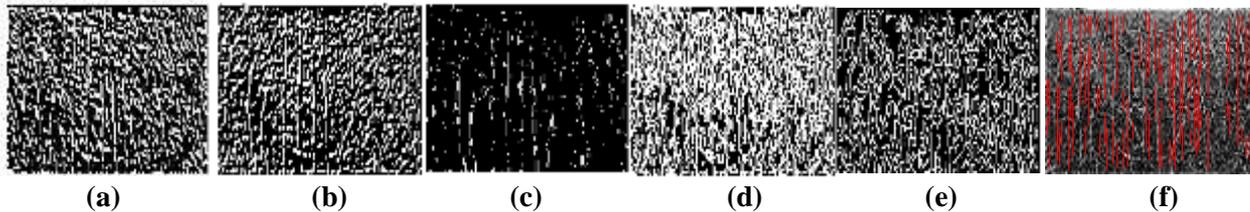


Figure 6: The Feature Extraction phase. (a) applies the diagonal line +45 to the lip print, (b) applies the diagonal line -45 to the lip print, (c) applies the vertical Sobel operator to the lip print, (d) combines the three operators for a lip, (e) applies Canny edge detection to the combined result, and (f) applies the HT analysis of straight lines to the combined result.

5.3 Features Selection:

The third phase is selecting features. After extracting features from lip prints, we applied GA, PSO, and WCA as FS to reduce features. We are using algorithms 1, 2, and 3, respectively. We used Eq. (10) in the three algorithms as the objective function.

$$\text{Max: } f(X_i) = \left(\frac{1}{n}\right) \sum_{j=1}^n X_{ij} \quad (10)$$

Where $f(X_i)$ = mean function, X_{ij} is the value of feature i per image, $n =$ No. of selected features by meta-heuristic methods.

This study used four lip prints for each person: three lip prints were used to create the pattern for training, and one lip print was used for testing. The pattern is created from three lip print images of the same person using Eq. (11).

$$I_{\text{pattern}}(x, y) = \begin{cases} 1 & \text{if } FS_1(x, y) + FS_2(x, y) + FS_3(x, y) \geq 2 \\ 0 & \text{if } FS_1(x, y) + FS_2(x, y) + FS_3(x, y) < 2 \end{cases} \quad (11)$$

Where: $I_{\text{pattern}}(x, y)$ is the pattern image for the person.

$FS_1(x, y)$, $FS_2(x, y)$, and $FS_3(x, y)$, the features for three lip prints for the same person after FS are collected using GA, PSO, and WCA, respectively.

5.4 Classification:

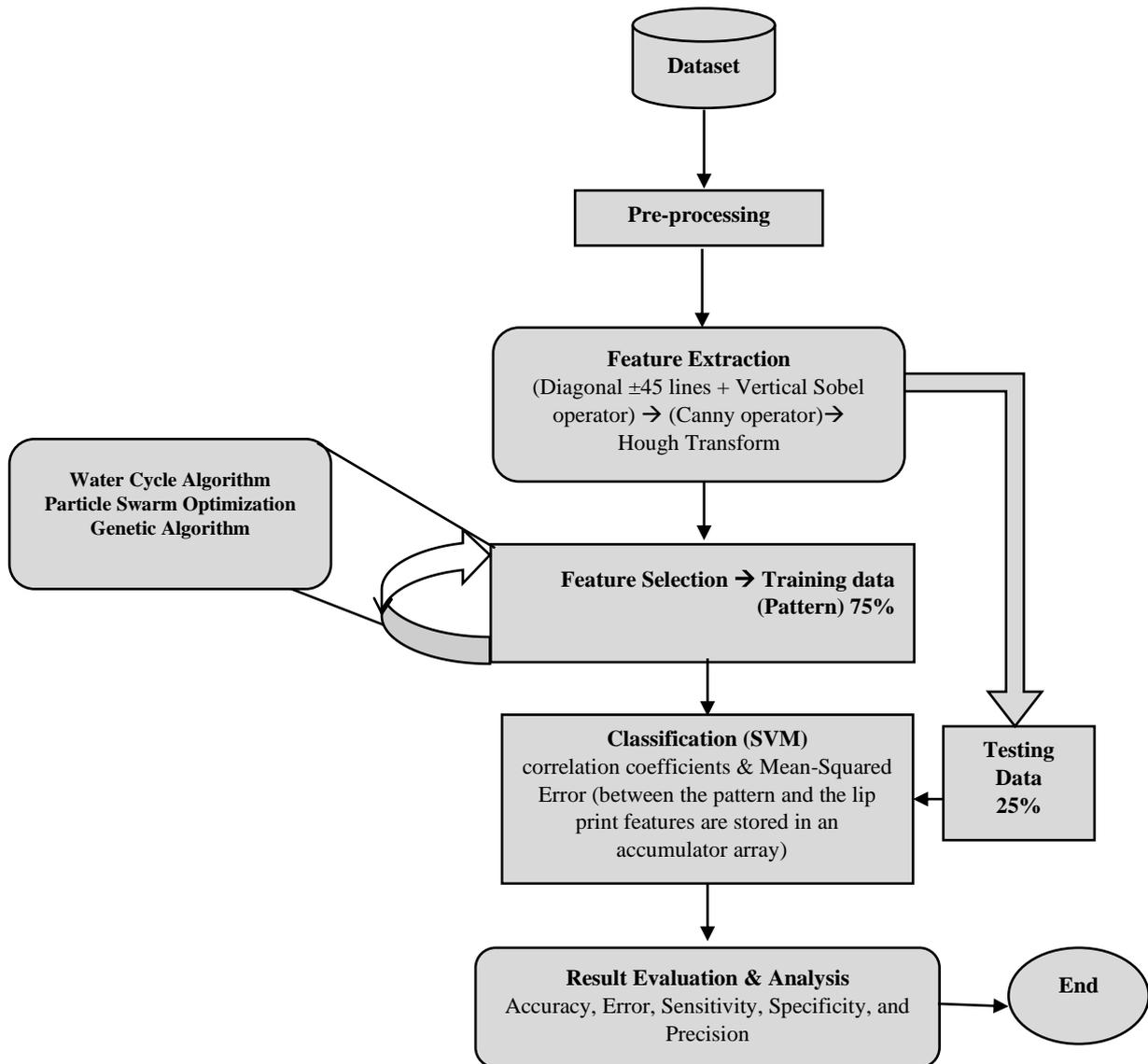


Figure 7: The Proposed Method Flowchart.

SVM is a popular learning algorithm in many research fields, including informatics, power systems, and bioinformatics. The FS from lip prints was fed into the SVM classifier to assess the robustness of the chosen features from the dataset. The objective of SVM is to divide different classes. The Holdout Method distributes the training and testing sets using cross-validation. The mean-square error (MSE) and correlation coefficients between the pattern and the lip print are stored in an accumulator array. In the fourth phase, correlation coefficients and MSE are fed into SVM to analyze and evaluate the proposed method to determine whether a lip print image belongs to the same person. Each dataset is randomly divided into 75% training and 25% testing. Each person's performance is averaged over 20 runs. The flowchart for the proposed method is shown in Figure 7.

6. Results and Discussion

This section evaluates the proposed method in terms of its performance as follows:

6.1 The evaluations of the proposed method

The evaluations were based on two types of criteria, as follows:

- First, we evaluated the effectiveness of the proposed method by selecting features using WCA, PSO, and GA. A classification algorithm is evaluated using metrics such as accuracy, error, sensitivity, precision, and real-time selection rate, as shown in Table 5. Higher accuracy, sensitivity, and precision rates indicate better classifier performance. Similarly, a lower error rate indicates the efficacy of the method. The evaluation measures are selected based on FS using meta-heuristic methods, as shown in Tables 6 and 7 for two datasets. In Figures 8 and 9, the performance analysis of WCA, PSO, and GA with SVM gives more accuracy in lip print classification for the datasets.
- The fitness values of WCA, PSO, and GA were compared in the second evaluation. Figure 10 shows an example of the comparison convergence curves of the best fitness for WCA, PSO, and GA. The convergence curves of the performance analysis of the best fitness for WCA, PSO, and GA for two datasets are shown in Figures 11 and 12, in which the WCA is ranked highest.

6.2 comparisons of the proposed method

These are the details of the comparisons, as follows:

- WCA is the best method to select the FS for lip print classification. WCA with SVM outperforms other methods because WCA has combined the characteristic PSO to select the best location and GA to get the optimal solution by using mutation that makes WCA give the best accuracy, followed by PSO and GA, as shown in Figures 11 and 12.
- In Table 6, the proposed method shows a better result when using meta-heuristics methods for feature selection with the dataset in [35], with average accuracy rates of 97.9%, 96.8%, and 95% for WCA, PSO, and GA, respectively. Table 8 compares methods using the same dataset as [35]. Compared to most other methods, the proposed method provides better accuracy; the compared methods do not employ meta-heuristic methods. Table 8 shows that the statistical method in [37] gives a high accuracy of 96% and uses 20 lip prints. Figure 13 compares WCA, PSO, and GA in terms of accuracy rate with other methods.
- According to Table 7, the dataset in [36] shows the proposed method gives high accuracy in WCA and PSO, but in GA, the result was close to the algorithm in [11]; the average WCA, PSO, and GA accuracy rates are 94.1%, 93.1%, and 91.9%, respectively.

Table 5: Evaluation Measures

Measures	Formula
Accuracy	$(TP + TN) / (TP + TN + FN + FP)$
Error	$(FP + FN) / (TP + TN + FN + FP)$
Sensitivity	$TP / (TP + FN)$
Precision	$TP / (TP + FP)$

True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN).

Table 6: Comparison the result of the proposed method and algorithm in [11] for dataset [35].

Meta-heuristic methods	Accuracy rate	Error rate	Sensitivity rate	Precision rate	Average Time. sec.
WCA	97.9%	2.1%	98.43%	98.43%	6.91
PSO	96.8%	3.2%	96.3%	95.9%	7.17
GA	95%	5%	96.16%	94.96%	7.02
Algorithm in [11]	93.6%	6.4%	98.64%	94.78%	16.54

Table 7: Comparison the result of the proposed method and algorithm in [11] for dataset [36].

Meta-heuristic methods	Accuracy rate	Error rate	Sensitivity rate	Precision rate	Average Time. sec.
WCA	94.1%	5.9%	94.1%	94%	17.44
PSO	93.1%	6.90%	92.80%	92.5%	17.48
GA	91.9%	8.10%	91.15%	90.35%	17.59
Algorithm in [11]	91.94%	8.06%	96.1%	95.5%	21.60

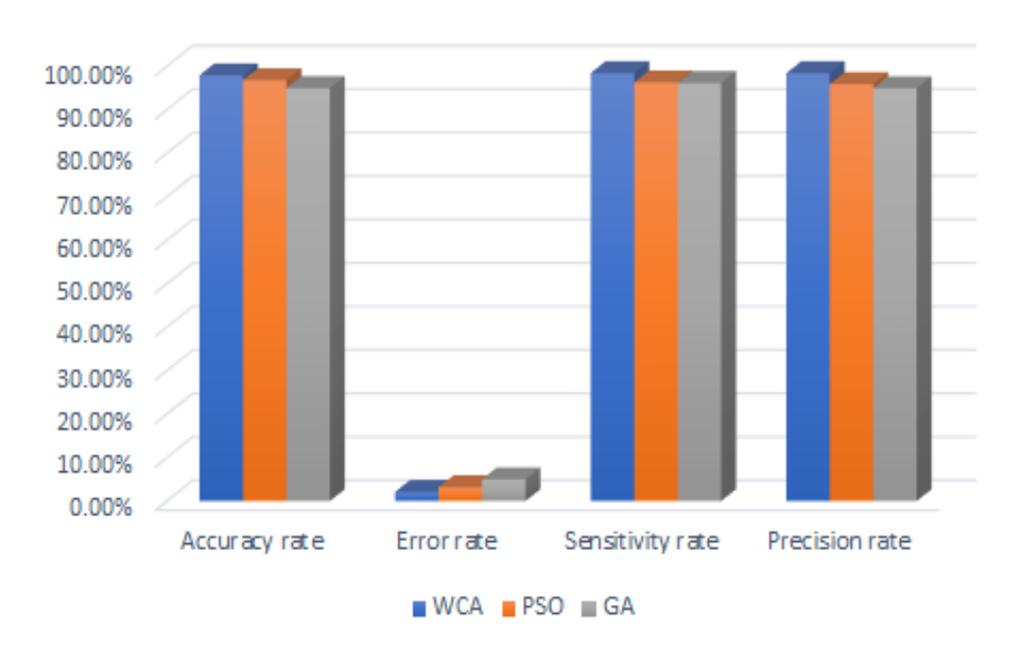


Figure 8: The SVM classifier uses WCA, PSO, and GA analysis for accuracy, error, sensitivity, and precision for dataset in [35].

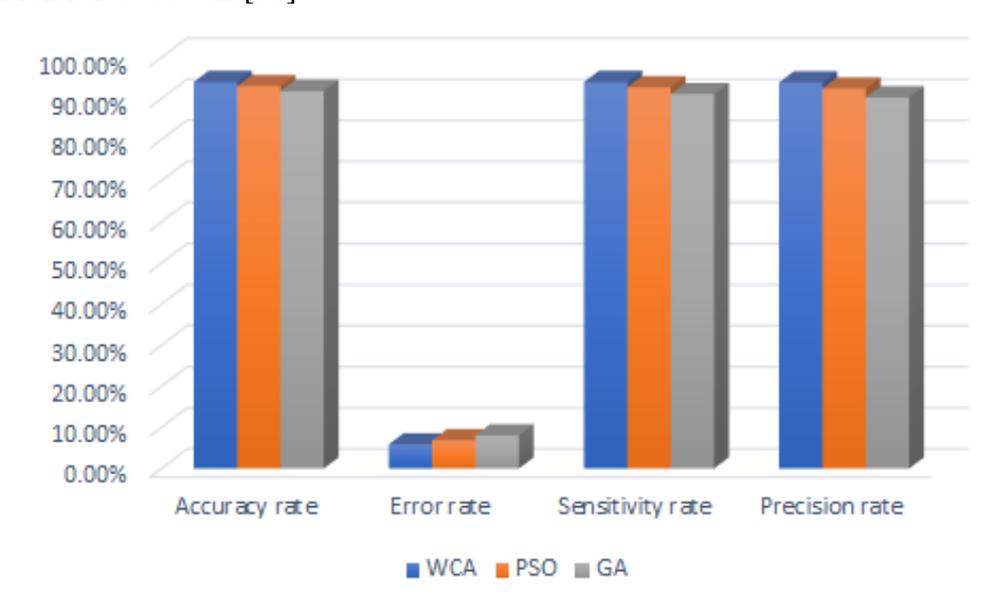


Figure 9: The SVM classifier uses WCA, PSO, and GA analysis for accuracy, error, sensitivity, and precision for dataset in [36].

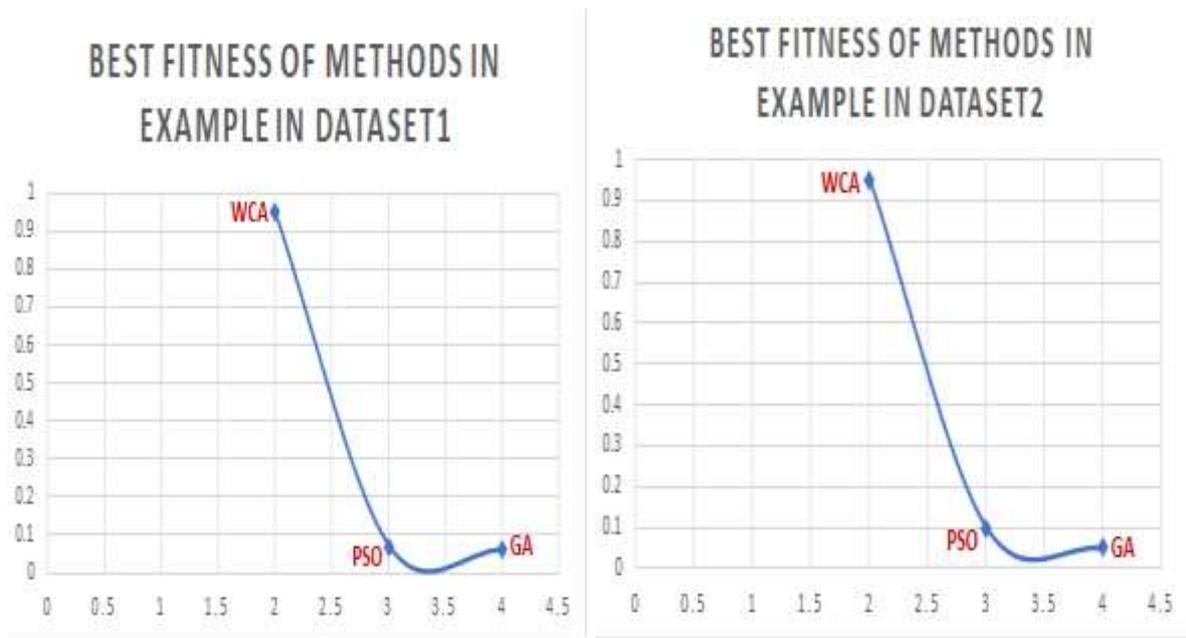


Figure 10: An example comparison of convergence curves of the best fitness for WCA, PSO, and GA.



Figure 11: Convergence curves of the best fitness for WCA, PSO, and GA for dataset [35]

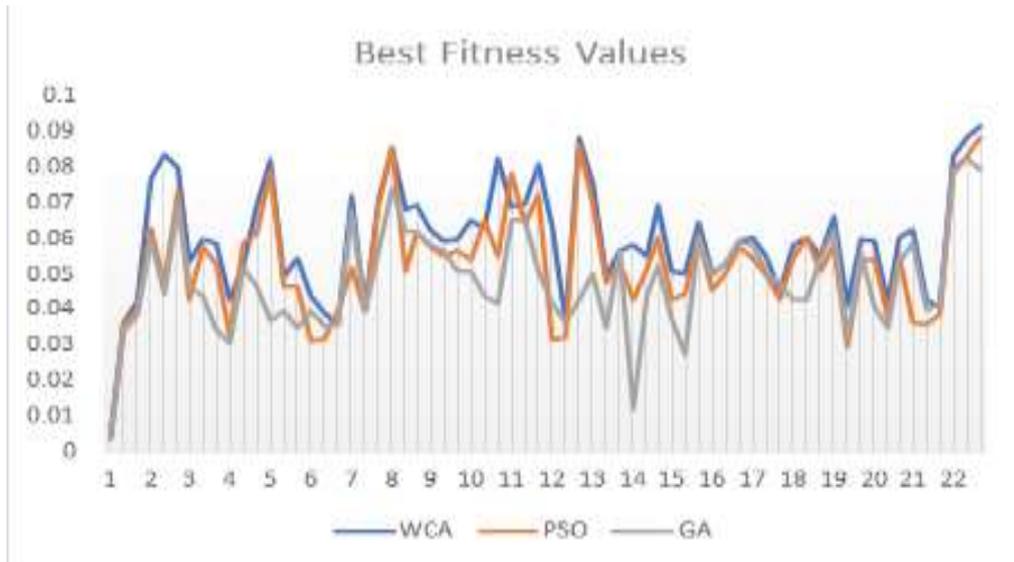


Figure 12: Convergence curves of the best fitness for WCA, PSO, and GA for dataset [36].

Table 8: A comparison between the proposed method and other methods using a dataset in [35]

Methods	Accuracy rate
FS (WCA)	97.9%
FS (PSO)	96.8%
FS (GA)	95%
Statistical method[37]	96 %
The algorithm in [38]	92.7 %
Bifurcation analysis [39]	77.0 %
Section Comparison[40]	85.1 %
DTW + Voting system[41]	88.5 %
DTW[42]	78.8 %
ROI + cross – correlation[43]	93%

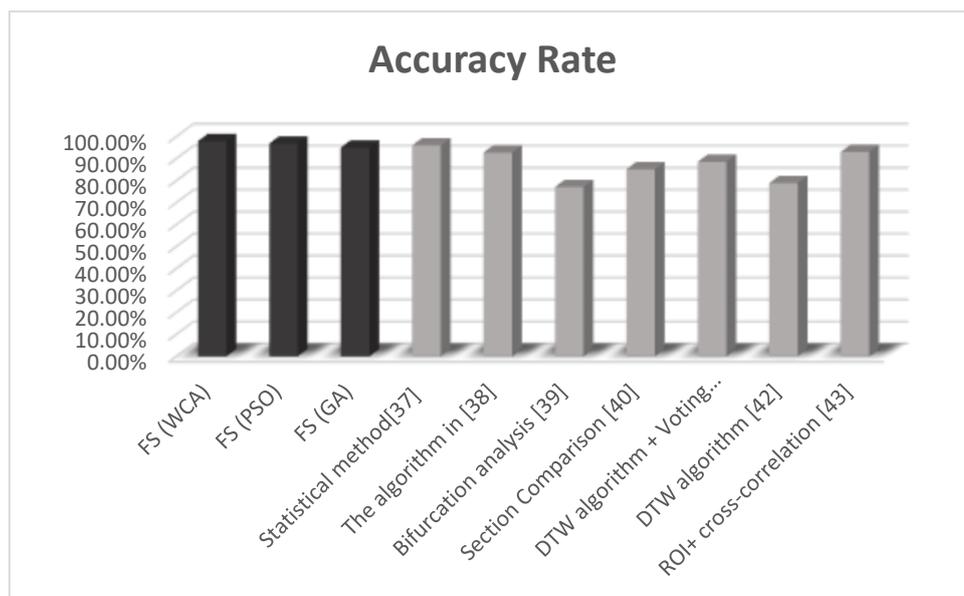


Figure 13: compares WCA, PSO, and GA in terms of accuracy rate with other methods for dataset [35]

7. Conclusion and Future Works

In this study, meta-heuristic methods are used to improve performance instead of traditional methods. Initially, the lip print image is pre-processed in many steps. Then, from the denoised image, a set of features is extracted. The dimensionality of the feature space can be further reduced by meta-heuristic methods such as GA, PSO, and WCA. Finally, SVM is used to classify lip prints and compare them with other techniques that do not use meta-heuristics. As a result of the method's collection of GA and PSO features, the WCA provided better accuracy. The results show that the lip print classification method had better accuracy, sensitivity, precision, and error rate. In the future, hybridization of the meta-heuristic methods will be performed to improve the accuracy of the classifier and use the proposed method in other pattern recognition problems.

References

- [1] H. Faris, M. Mafarja, A. A. Heidari, and I. Aljarah, "An Efficient Binary Salp Swarm Algorithm with Crossover Scheme for Feature Selection Problems," *Knowledge-Based System*, vol. 154, no. 15, pp. 43–67, 2018.
- [2] N. Fouad and H. Sarab, "Genetic Algorithm based Clustering for Intrusion Detection," *Iraqi Journal Science*, vol. 58, no. 2B, pp. 929–938, 2017.
- [3] S. Kashef and H. Nezamabadi-pour, "A new feature selection algorithm based on binary ant colony optimization," in *Proceedings of the 5th Conference on Information and Knowledge Technology*, May, 2013.
- [4] M. Parham and G. Mozghan, "A hybrid particle swarm optimization for feature subset selection by integrating a novel local search strategy," *Applied Soft Computing*, vol. 43, pp. 117–130, 2016.
- [5] P. Ghosh, A. Karmakar, J. Sharma, and S. Phadikar, "CS-PSO based Intrusion Detection System in Cloud Environment," in *Proceedings of the Emerging Technologies in Data Mining and Information Security*, Springer Singapore, 2019.
- [6] P. Swarna et al., "An effective feature engineering for DNN using hybrid PCA-GWO for intrusion detection in IoMT architecture," *Computer Communications*, vol. 160, no. 1, pp. 139–149, 2020.
- [7] M. Mayuranathan, M. Murugan, and V. Dhanakoti, "Best features based intrusion detection system by RBM model for detecting DDoS in cloud environment," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 3, pp. 3609–3619, 2021.
- [8] E. Ahmed, M. Reham, G. Rania, and G. Marwa, "Improved seagull optimization algorithm using Lévy flight and mutation operator for feature selection," *Neural Computing and Applications*, vol. 34, pp. 7437–7472, 2022.
- [9] P. Kandhway and A. Kumar, "A Water Cycle Algorithm-Based Multilevel Thresholding System for Color Image Segmentation Using Masi Entropy," *Circuits, Systems, and Signal Processing*, vol. 38, no. 7, pp. 3058–3106, 2019.
- [10] E. Hadi, S. Ali, B. Ardeshir, and H. Mohd, "Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems," *Computers & Structures*, vol. 110–111, pp. 151–166, 2012.
- [11] A. Tamara, Afif, M. Samira, S., and M. Mostafa-Sami, M., "Personal identification using lip print furrows," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 1, pp. 460–468, 2023.
- [12] I. M. El-Hasnony, S. I. Barakat, M. Elhoseny, and R. R. Mostafa, "Improved Feature Selection Model for Big Data Analytics," *IEEE Access*, vol. 8, no. 99, pp. 66989–67004, 2020.
- [13] L. Xiang, Z. Deng, and A. Hu, "Forecasting Short-Term Wind Speed Based on IEWT-LSSVM Model Optimized by Bird Swarm Algorithm," *IEEE Access*, vol. 7, pp. 59333–59345, 2019.
- [14] E. H. Houssein, M. M. Ahmed, M. A. B. D. Elaziz, A. A. Ewees, and R. M. Ghoniem, "Solving Multi-Objective Problems Using Bird Swarm Algorithm," *IEEE Access*, vol. 9, pp. 36382–36398, 2021.
- [15] J. Bhardwaj and N. Abhijit, "Medical image fusion using lifting wavelet and fractional bird swarm optimization," in *Proceedings of the International e-Conference on Intelligent Systems and Signal*

- Processing, Gujarat, India, 28–30 December 2020; Springer: New York, NY, USA, 2022.*
- [16] K. Mishra and S. K. Majhi, “A binary Bird Swarm Optimization based load balancing algorithm for cloud computing environment,” *Open Computer Science*, vol. 11, no. 1, pp. 146–160, 2021.
- [17] D. S. Javier et al., “Bio-inspired computation: Where we stand and what’s next,” *Swarm and Evolutionary Computation*, vol. 48, pp. 220–250, 2019.
- [18] N. Ansari, “A Survey on Feature Selection Techniques using Evolutionary Algorithms,” *Iraqi Journal Science*, vol. 62, no. 8, pp. 2796–2812, 2021.
- [19] C. Zhang, J. Zhou, C. Li, W. Fu, and T. Peng, “A compound structure of ELM based on feature selection and parameter optimization using hybrid backtracking search algorithm for wind speed forecasting,” *Energy Conversion and Management*, vol. 143, pp. 360–676, 2017.
- [20] G. Dhal, K. J. Gálvez, S. Ray, A. Das, and S. Das, “Acute lymphoblastic leukemia image segmentation driven by stochastic fractal search,” *Multimedia Tools and Applications*, vol. 79, pp. 12227–12255, 2020.
- [21] V. Tiwari, “Face recognition based on cuckoo search algorithm,” *Indian Journal of Computer Science and Engineering*, vol. 3, no. 3, pp. 401–405, 2012.
- [22] A.-C. Sgârciu and V. Enache, “A feature selection approach implemented with the binary bat algorithm applied for intrusion detection,” in *Proceedings of the 38th Int. Conf. Telecommun. Signal Process. (TSP)*, 2015.
- [23] P. Sharma, S. Sundaram, M. Sharma, A. Sharma, and D. Gupta, “Diagnosis of Parkinson’s disease using modified grey wolf optimization,” *Cognitive Systems Research*, vol. 54, pp. 100–115, 2019.
- [24] H. T. Ibrahim, W. J. Mazher, O. N. Ucan, and O. Bayat, “Feature selection using salp swarm algorithm for real biomedical datasets,” *International Journal of Computer Science and Network Security*, vol. 17, no. 12, pp. 13–20, 2017.
- [25] S. Jabbar and S. Z. Zainudin, “Water cycle algorithm for attribute reduction problems in rough set theory,” *Journal of Theoretical and Applied Information Technology*, vol. 61, no. 1, pp. 107–117, 2016.
- [26] M. Parham and G. Mozghan, “A hybrid particle swarm optimization for feature subset selection by integrating a novel local search strategy,” *Applied Soft Computing*, vol. 43, pp. 117–130, 2016.
- [27] K. Mistry, L. Zhang, S. C. Neoh, C. P. Lim, and B. Fielding, “A Micro-GA Embedded PSO Feature Selection Approach to Intelligent Facial Emotion Recognition,” *IEEE Transactions on Cybernetics*, vol. 47, no. 6, pp. 1496–1509, 2017.
- [28] C. Ke, Z. Feng-Yu, and Y. Xian-Feng, “Hybrid particle swarm optimization with spiral-shaped mechanism for feature selection,” *Expert Systems with Applications*, vol. 128, pp. 140–156, 2019.
- [29] M. Majdi, A. Ibrahim, F. Hossam, H. Abdelaziz, A.-Z. Ala’ M., and M. Seyedali, “Binary grasshopper optimisation algorithm approaches for feature selection problems,” *Expert Systems with Applications*, vol. 117, no. 1, pp. 267–286, 2019.
- [30] H. Rahul and K. Harjot, “Hybrid binary Sine Cosine Algorithm and Ant Lion Optimization (SCALO) approaches for feature selection problem,” *International Journal of Computational Materials Science and Engineering*, vol. 9, no. 1, pp. 1950021-1950030, 2020.
- [31] T. Bhattacharyya and B. Chatterjee, “Mayfly in Harmony : A New Hybrid Meta-Heuristic Feature Selection Algorithm,” *IEEE Access*, vol. 8, pp. 195929–195945, 2020.
- [32] K. Ludmila, “Genetic algorithm for feature selection for parallel classifiers,” *Information Processing Letters*, vol. 46, no. 4, pp. 163–168, 1993.
- [33] Y. Shi and R. Eberhart, “A Modified Particle Swarm Optimizer,” in *Proceedings of the IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98TH8360)*, June, 1998.
- [34] A. Sadollah, H. Eskandar, H. Min, D. Guen, and J. Hoon, “Water cycle algorithm : A detailed standard code ScienceDirect Water cycle algorithm : A detailed standard code,” *SoftwareX*, vol. 5, pp. 37-43, 2016.
- [35] W. Krzysztof and D. Rafal, “W. Krzysztof, and D. Rafal,” *Lip prints database, Mendeley Data, V1*, 2021. [Online]. Available: doi:10.17632/yjxxv9xbds.1
- [36] D. Mrozek, E. Ostalowska, and B. Małysiak-Mrozek, “A database of lips traces,” *IEEE-dataport*, 2018. [Online]. Available: doi: 10.21227/H2R04P
- [37] B. Saptarshi, A. S, and K. Samir, “Personal Identification from Lip-Print Features using a Statistical Model,” *International Journal of Computer Applications*, vol. 55, no. 13, pp. 30–34, 2012.

- [38] K. Wrobel, R. Doroz, P. Porwik, and M. Bernas, "Personal identification utilizing lip print furrow based patterns. A new approach," *Pattern Recognition*, vol. 81, pp. 585–600, 2018.
- [39] W. Krzysztof, D. Rafal, and P. Malgorzata, "Lip Print Recognition Method Using Bifurcations Analysis," in *Proceedings of the 7th Asian Confer. on Intelligent Information and Database Syst., Bali, Indonesia*, 2015.
- [40] W. Krzysztof, D. Rafal, and P. Malgorzata, "A Method of Lip Print Recognition Based on Sections Comparison," in *Proceedings of the International Conference on Biometrics and Kansei Engineering (ICBAKE)*, Japan, pp. 47-52, 2013.
- [41] P. Porwik and T. Orczyk, "DTW and Voting-Based Lip Print Recognition System," in *Proceedings of the Eleventh IFIP TC 8 Intern.Confer. Computer Informa. Syste and Indust. Manage., Venice, Italy*, 2012.
- [42] S. Lukasz, W. Krzysztof, and P. Piotr, "Lip print recognition based on DTW algorithm," in *Proceedings of the Third World Congress on Nature & Biolog. Inspired Compu., Salamanca, Spain*, 2011.
- [43] W. Krzysztof, P. Piotr, and D. Rafal, "Effective Lip Prints Preprocessing and Matching Methods," in *Proceedings of the 9th International Conference on Computer Recognition Systems CORES, Advances in Intelligent Systems and Computing 403*, 2016.