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The Recognition of Latent Fingerprints using Swarm Intelligence based Hybrid Approach

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ABSTRACT: Latent fingerprints contribute a vital role to narrow down criminal suspects. The border securities, law enforcement agencies, and forensic departments use the latent finger impressions to identify the culprit. The captured fingerprints are generally attained in bad quality with a lot of background image noise which makes it difficult for the forensic agencies to process for the matching. There is the availability of numerous state of the art techniques for the recognition of latent fingerprints. Most of the existing techniques lack to find the accurate match of the latent fingerprints due to its poor quality of the images and dependability on a single classifier. The efficient automated system is required to find an accurate match so that innocent should not be apprehended. This research paper has proposed the hybrid swarm intelligence based automated approach to improve the recognition rate of latent fingerprints matching. The automated approach is the hybridization of cuckoo search and particle swarm optimization algorithms with evaluation using the research database of NIST Special Database 27. The hybridized approach adapts the advantageous attributes of both the techniques. The database is distributed in three categories of Good, Bad, and Ugly based on the quality of latent finger impressions. The hybrid approach is applied to all the types of images and comparison is conducted with existing techniques by evaluating the identification performance. The proposed hybrid algorithm has attained an average recognition rate of 91.38%. The results evaluated as the identification rate outperformed in comparison with existing techniques.

Keywords: Finger Impressions, Latent Fingerprints, Swarm Intelligence, Particle Swarm Optimization, Cuckoo Search, Crime Scene, Criminal Detection, Fingerprint Matching.

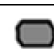
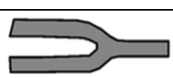
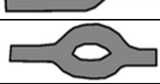
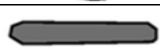
Abbreviations: NIST, national institute of standards and technology; SI, swarm intelligence; CS, cuckoo search; PSO, particle swarm optimization; NMD, neighboring minutiae-based descriptor; DCNN, deep convolutional neural network; SVM, support vector machine; ANFIS, adaptive neuro fuzzy inference system.

I. INTRODUCTION

The adaptation of fingerprint as the successful attribute to define the human identity has extended the scope of finger impressions for research aspects. The widest usage of fingerprints is considered in the field of criminologist aspects to determine the identity of the culprit. Fingerprints are composed of different patterns available in the outer tissue layer at the end of the fingers (fingertips). These patterns are the minutiae features such as dots, delta, core, ridge enclosure, ridge endings, independent ridge, and bifurcation. In simple terms, minutiae are the patterns of ridges and valleys available on the fingers. Each person owns unique finger patterns [1]. The different types of minutiae features are presented in Table 1.

The fingerprint possesses three types of main patterns such as whorl, loop, and arch. The further extension of these patterns can also be noticed with mixed patterns. The major usage of fingerprints is to define human identity. There are numerous applications of fingerprints as successful biometric system in smartphones, corporate offices, defense security, healthcare, border controls, and many more. The finger impressions are generally recorded in the formats of plain and rolled. Plain fingerprints are recorded by applying the ten-print fingertips directly on the surface and rolled fingerprints are recorded by applying nail to nail impressions respectively. Apart from the plain and rolled fingerprints, the fingerprints captured during the crime scenes are known as latent fingerprints. The plain and rolled fingerprints are used to find the match for the latent fingerprints.

Table 1: Minutiae features of the Fingerprint [1].

	Termination		Point or Island
	Bifurcation		Spur
	Ridge Enclosure		Crossover
	Independent Edge		

Latent fingerprints have become the fundamental element for law enforcement agencies to identify the crime suspect after the first time usage of latent fingerprints as evidence in the year 1893 by the Argentina government [2]. It is difficult to attain the latent fingerprints of good quality as these are the accidentally left finger impressions. There are numerous existing research studies in which the researchers majorly focused on the enhancement of the latent fingerprint images. Xu *et al*., [3] have used the Gabor filter along with the minutiae dictionary for the enhancement of the latent fingerprints. Initially, the texture details have been extracted and further, the orientation fields are utilized along with the considered concepts for the enhancement of minutiae of the latent finger images. Makhija *et al.,* [4] have used different methods for the enhancement of latent fingerprints. The authors have compared the methods of histogram equalization, binarization approach with median filter, and wiener filter for the enhancement of latent fingerprints based on different performance metrics. Li *et al.,* [5] have utilized the deep convolutional neural network and presented the method of Finger Net for the enhancement of latent fingerprints. The overall fingerprints were enhanced for the end to end and pixel to pixel learning the neural network. Joshi et al. [6] have proposed the model of generative adversarial network to enhance the latent fingerprints with major focus on the improvement of the ridge structure of the minutiae features. Lokaksha and Gaikwad [7] have proposed the model based on the time variance with the Gabor and sparse representation to improve the quality of latent fingerprint images. The method improves the ridge structure and reduces the noise value.

There are also numerous other studies for the improvement of the quality of latent fingerprints but somehow the existing systems lack at some point to improve the ridge information and orientation fields. The present study utilizes the dictionary-based approach along with the Gaussian filter to enhance the quality of latent fingerprints. The ridge information and the field of orientation are the key components to find the accurate match of latent fingerprints. The major focus of the research paper is on the recognition of the latent fingerprints which is conducted using the hybrid approach of cuckoo search and particle swarm optimization.

The algorithms of cuckoo search and particle swarm optimization are swarm intelligence based concepts. Swarm intelligence techniques are inspired from the working behaviour social species [8-11]. Cuckoo search (CS) was proposed by Yang and Deb [12] by imitating the attributes of cuckoo agents. The CS algorithm was developed to attain the optimized solutions of continuous problems. The cuckoo agents obey the attribute of brood parasitic to store their egg in other bird's nest which was considered as the key inspiration for the CS algorithm. On the other hand, particle swarm optimization (PSO) was developed by Eberhart and Kennedy by imitating the attributes of the school of fishes and flying birds flock [13]. The PSO algorithm the particles are the artificial agents assumed from the flying birds or floating fishes. There are two optimization factors in the PSO algorithm: local and global search based optimizations. The optimized solution attained by the individual particle agents is referred to as the local optimization and overall group based solution attained by sharing experience is referred to as global optimization. The algorithm works in an iteration based manner to attain the overall global best solution. The particles initialize the process with a random movement with a velocity. Further, the change in position and velocity are evaluated. The overall best solution is stored after the end of the iterations with global optimization. The algorithm of particle swarm optimization enhances the individual attribute of the cuckoo agent to determine the efficient match. The dataset of NIST special database 27 is used for the experimentation. The proposed hybrid algorithm has attained the average recognition rate of 91.38% which is the dominant performance of the proposed hybrid algorithm as compared to existing techniques.

The organization of the other sections of the paper is mentioned here: Section II illustrates the prior work on the recognition of latent fingerprints. Further, Section III demonstrates the proposed research methodology of hybrid cuckoo search and particle swarm optimization for the identification of match for the latent fingerprints. The section also illustrates the workflow of the proposed hybrid concept. Section IV describes the performance analysis based on the evaluated results and comparison with existing techniques. The conclusion of the paper is discussed in section V and future scope in Section VI respectively.

II. PRIOR WORK

In this section, the prior literature work related to the recognition of latent fingerprints is described. There is the adaptability of different techniques by different researchers for the matching process of latent fingerprints with their respective complete ten-print images. The latest research studies are considered to have a review of the prior work related to the latent fingerprints recognition.

Karar and Kaur [14] have used the watershed recognition algorithm for the identification of latent fingerprints. The authors have also improved the feature set by considering multiple watershed segmentation technique. The method of anisotropic filter has been utilized for image enhancement. Further, the authors Medina-Pérez *et al*., [15] proposed three different versions of cluster of minutiae matching algorithms to handle the distortions of latent fingerprints and identification of latent fingerprints. The proposed version includes the Minutia Cylinder-Codes, Minutia m-triplets, and neighboring minutiae-based descriptor (NMD). In the overall scenario, the authors have reported better performance results of proposed clustering based algorithms in comparison with their respective versions. Silpamol and Thulasidharan [16] focused on the detection and rectification of distorted fingerprints before the final matching of latent fingerprints. The authors have utilized the dictionary-based approach for prior information utilization. The final latent fingerprint matching was performed based on the pose, orientation, and dictionary lookup. Aravindan and Anzar [17] have initially prepared the research database of fingerprints as MES College of Engineering Fingerprint (MESCEF). The authors have captured the fingerprint impressions of 125 individuals and produced 2500 images. The research methodology of Wavelet SIFT (Scale Invariant Feature Transform) has been proposed for fingerprint recognition. The major purpose of the work was to produce the alignment-free research approach.

Furthermore, Cao and Jain [18] have introduced the concept of virtual texture templates for the improvement of latent fingerprint recognition. The analysis results indicate the improvement of 8.9% of rank-1 accuracy in comparison with the existing techniques. Venkatesh *et al.*, [19] considered the adaptive neuro-fuzzy inference system (ANFIS) for the recognition of latent fingerprints. The authors have reported the effective result for the proposed ANFIS technique as compared to the considered existing techniques. Ezeobiejesi and Bhanu [20] have used the infusion of patches and minutiae-based latent fingerprint recognition approach. The similarity was determined with the learning on both the patches & minutiae and only with the usage of patches for the learning. The evaluation results indicate the superiority of the proposed technique with rank-1 identification rate of 81.35% which was earlier 74% in the existing concepts. Jindal and Singla [21] used the nature-inspired computing concept of the cuckoo search algorithm for the matching of latent fingerprints with rolled fingerprints. The minutiae-based finger features were utilized for the matching. Pavithra and Suresh [22] have used the deep convolutional neural network (CNN) for the identification of latent fingerprints. The experimentation results indicate the superior performance identification accuracy of the proposed CNN approach (80% identification accuracy) in comparison with the SVM classifier.

The discussed prior work related to latent fingerprint recognition indicates the usability of different research methodologies for the recognition of latent fingerprint with different criteria of experimentation. The major research gap analyzed in the discussed work for the lack of performance efficiency is the usability of a single research method for the classification. There is a higher probability of the individual approach to lack in performance as compared to hybrid approaches. So, there is the need for efficient research techniques to apprehend the criminal on the basis of latent fingerprint information as the misleading information can lead to apprehending an innocent and release of a culprit. In this research work, a hybrid approach of cuckoo search (CS) and particle swarm optimization (PSO) is proposed for the recognition of latent fingerprints.

III. RESEARCH METHODOLOGY

In this research paper, the latent fingerprints recognition process is conducted using the proposed hybrid algorithm of CS and PSO. The hybrid approach overcomes the drawbacks of individual algorithms. In the PSO algorithm, particles work as the local and global agents to determine the individual best and overall best solutions respectively. In the CS algorithm, cuckoo agents work individually to determine both types of the individually best and overall optimal solution. The cleaver behaviour of cuckoo agents to store their egg in other bird's best makes them appropriate to determine the individually best solution. The particles in the PSO algorithm can lack during the process of exploration and exploitation. The balance among the exploration and exploitation should be maintained to determine the overall optimal solution. The hybrid proposed algorithm overcomes the demerits of the PSO algorithm for the possibility of trapping during the local search by adapting the attributes of the cuckoo search to evaluate the local best solution. On the other side, the individual cuckoo agents can be lacks to determine the overall global best solution. The proposed hybrid algorithm of CS and PSO can add up the merits of both the algorithms to achieve the optimal match for the latent fingerprints. The process of latent fingerprints matching with original fingerprints involves the steps of segmentation, enhancement, binarization, minutiae-based features extraction, features filtration by removing the spurious minutiae, and final matching using hybrid CS & PSO algorithm. The workflow of the research methodology is illustrated in Fig. 1. The research process in a stepwise manner is described here.

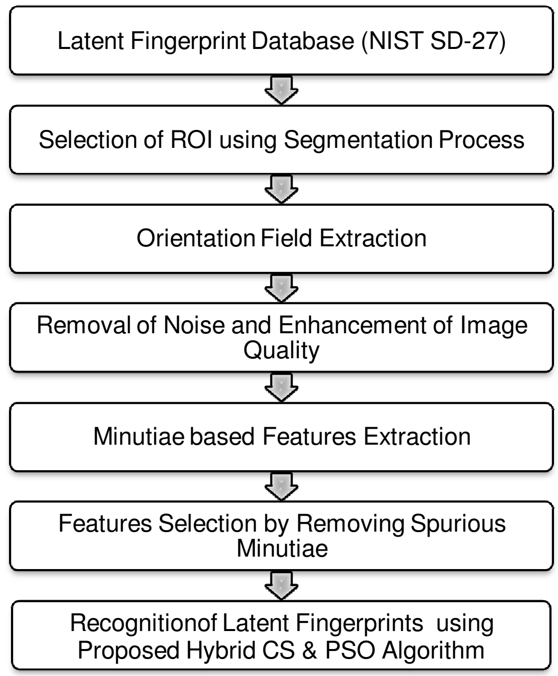


Fig. 1. Workflow of Latent Fingerprints Recognition.

A. Latent Fingerprint Database

In this research work, the research experimentation has been conducted on the latent fingerprint images from the NIST special database 27 [23]. The overall dataset consists of a total of 258 latent fingerprints in three quality images of good, bad, and ugly along with their respective 258 rolled fingerprints. There are 88 images of Good quality and 85 images of both the Bad & Ugly quality each.

B. Segmentation

The considered latent fingerprint images are segmented to select the appropriate region of interest and removal of background noisy region. The segmentation is performed by considering finger images into the format of pixel matrix blocks. The selection of pixel blocks is conducted based on the threshold variance evaluated for each block. The value higher than the threshold is considered as the region of interest. The variance of blocks can be evaluated as illustrated in Eq. (1).

$$\text{variance (block)} = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(I(i,j)-Mean(block))^2}{n^2} \quad (1)$$

Where, *I (i,j)* indicates the pixel position, and *Mean (block)* is the mean greyscale value of block of the considered pixel matrix.

C. Enhancement

The enhancement of the segmented region is important to enhance the ridge information and reduce the noise value of the background surface. The enhancement of the pixel images is conducted using the Gaussian filter along with the usage of dictionary approach. The initial step of the process is to estimate the orientation field of the finger images with the help of available ridge information in the dictionary. The local orientation field (L_o) can be extracted as presented in Eq. (2).

$$L_o(i,j) = \frac{1}{2}\tan^{-1}\frac{O_x(i,j)}{O_y(i,j)} \quad (2)$$

Where, $O_x(i,j)$ and $O_y(i,j)$ indicate the local orientation in the directions of *x* and *y* respectively with respect to their gradient values.

The extracted orientation field with the help of a dictionary is stored and images are further considered to improve the quality of ridge structures. Gaussian filters are effective to remove the noise values and highly significant to improve the edge information. The higher the value of variance indicates the higher possibility to smoothen and enhance the pixels. The Gaussian function (*G(x)*) can be illustrated as Eq. (3) to enhance the pixels' values.

$$G(x) = \left[\frac{1}{\sqrt{2\pi.variance}}exp^{-\frac{(x-Mean)^2}{2.variance\ (block)}}\right] \quad (3)$$

D. Binarization

The enhanced images are further binarized based on the fixed threshold value approach. The binarization process converts the grey scale images of possible values 0-255 into the black-white images of possible values 0 and 1 respectively. The formulation for the fixed binarization approach with threshold value *T* is illustrated in Eq. (4).

$$G(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq T \\ 0 & \text{Otherwise} \end{cases} \quad (4)$$

E. Minutiae based Features Extraction

The process of feature extraction involves the extraction of minutiae-based features from the latent fingerprints. The matching process is conducted based on the extracted appropriate features. The feature set involves the identification of normal pixel, ridge bifurcation, and ridge ending from the binarized image. This identification can be performed by using the method discussed by Jindal and Singla [21]. The approach considers the entire image pixels as the 3 × 3 matrix each time to select among the normal pixel, ridge ending, or bifurcation point. This can be illustrated more precisely by considering a binarized image with matrix values as shown in Table 2.

The values indicated in the matrix table of the image illustrates the different minutiae types in the combination of the 3 × 3 matrix. The colors of the 3 × 3 matrix as green, red, and blue are illustrating the normal pixel, ridge bifurcation, and ridge ending respectively

Table 2: An Image based Matrix Values with Minutiae Features.

0	0	0	0	0	1	0	0
0	0	1	0	1	1	0	0
0	1	0	1	0	0	1	0
1	0	0	1	0	1	0	0
0	0	1	0	0	0	1	0
0	1	0	1	0	1	0	0
0	1	0	0	1	0	1	0
0	0	1	0	0	1	0	0
0	1	0	1	0	1	0	0
0	0	0	0	0	0	0	0

F. Features Selection

The process of feature selection involves the selection of only the useful minutiae features that can be considered to identify the match for latent fingerprints. During the feature extraction process, the spurious minutiae features can also be extracted such as break, merge, ladder, dot, island, lake, triangle, etc. Such kinds of minutiae are spurious minutiae and are useless for the matching process. The consideration of such minutiae can lead to mismatching of latent fingerprints. So, a feature selection approach selects the appropriate features and discards the other features.

G. Matching

The matching of the latent fingerprints to determine the accurate match with the complete fingerprints is conducted using the proposed hybrid CS and PSO algorithm. The hybrid approach adapts the merits of both the algorithms and avoids lacking attributes. The processed binarised images are used for the matching of latent fingerprints with the original ten-print images. The step-wise procedure is mentioned below.

G(1). Consider the processed binarised latent fingerprint and complete fingerprint images.

G(2). The hybrid algorithm begins by initializing the particle swarm optimization algorithm as an overall research exploration strategy. The particles of the PSO algorithm attain the attributes of the CS algorithm to conduct the local search.

G(3). The initialization position and velocity of particles is considered as vectors as $V_i = [v_i^1, v_i^2, \dots, v_i^d]$ and $X_i = [x_i^1, x_i^2, \dots, x_i^d]$ respectively for the i^{th} particle in the *d* dimensions.

G(4). The attributes of CS are adapted by the PSO algorithm to determine the local search process as the best nest to store the cuckoo eggs. Here, the image pixels of latent fingerprint with minutiae information matching with minutiae of complete fingerprints are considered as the best host nest for the cuckoo agent to store egg. The formulation of CS to determine the solution is illustrated by Eq. (5).

$$x_i^{t+1} = x_i^t + \alpha \oplus L\acute{e}vy\ (\lambda) \quad (5)$$

Where, $L\acute{e}vy = t^{-\lambda}$, $(1 < \lambda \leq 3)$, *α* is the step size with considered value as *O(1)*, and ⊕ indicate the entry wise multiplication. The determined best nests as the best solution are acquired by the particles of PSO for further processing.

G(5). The position and velocity of the particles are updated as per the particle movement. The updated position and velocity can be evaluated in dimensions d as described in Eq. (6) and Eq. (7) respectively.

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \qquad (6)$$

$$V_i^d(t+1) = \omega V_i^d(t) + c_1 r_1^d\left(P_i^d(t) - X_i^d(t)\right) + c_2 r_2^d\left(P_g^d(t) - X_i^d(t)\right) \qquad (7)$$

Where, ω is the inertia weight with value within [0, 1]. c_1 and c_2 are the acceleration constants with positive values. r_1^d and r_2^d are the uniform random numbers with values within [0, 1] in dimension d. P_i^d and P_g^d indicate the position of an individual i^{th} particle and global swarm particles respectively in d dimensions with the best fitness value.

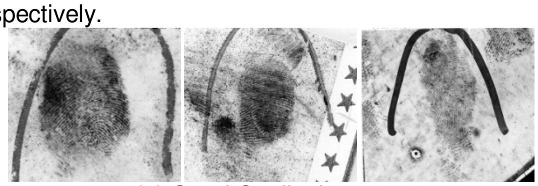
G(6). The overall attained solutions by different particles are stored and a global search is conducted by evaluating the best solution match for the latent fingerprints based on the minutiae information.

G(7). The overall best solution is obtained with a global search strategy using this hybrid approach.

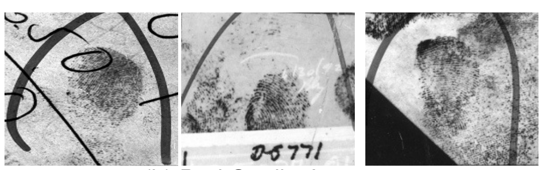
G(8). The hybrid algorithm tries to attain the best solution until the termination criteria of maximum considered iterations.

IV. EXPERIMENTATION AND ANALYSIS

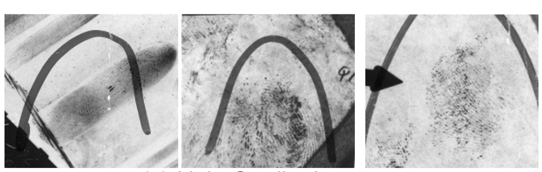
The performance of the proposed hybrid CS and PSO algorithm is analyzed by experimentation on NIST SD-27 Database. The database consists of three different categories of fingerprint images based on the quality of images as good, bad, and ugly. The sample images of the aforementioned categories are illustrated in Fig. 2(a)-(c). The good, bad, and ugly quality images of the NIST dataset are presented in Fig. 2 (a), (b), (c) respectively.



(a) Good Quality Images.



(b) Bad Quality Images.



(c) Ugly Quality Images.

Fig. 2. (a)-(c): Sample Images of Different Categories of NIST Special Database 27.

The performance comparison is conducted in terms of the identification rate. The identification rate is considered as the matching parameter to find the accurate match for the latent fingerprints. This accurate match is defined as the minutiae-based similarity between the latent fingerprints and their matching complete fingerprints. The similarity score found to be more than 75% is considered as the accurate match for the latent fingerprints. So, the identification rate can be defined as the ratio of the accurate match of latent fingerprints to the total number of fingerprint images. The identification rate and similarity scores are evaluated in the category wise manner of NIST SD-27 Database. The categories of good, bad, and ugly consist of 88, 85, and 85 images respectively. The similarity score of the proposed hybrid CS and PSO algorithm is evaluated in table 3. The proposed hybrid CS & PSO algorithm have attained the similarity score of 95.98% for the Good, 88.43% for the Bad, and 86.02% for the Ugly categories of NIST SD-27 dataset respectively. The table 3 also illustrates the comparison of hybrid technique with individual CS algorithm based on similarity scores. Jindal and Singla [21] have used the individual CS algorithm to determine the similarity score for the latent fingerprints with original ten-prints of NIST SD-27 dataset. The authors [21] have attained the similarity score values of 94.50% for the Good, 86.22% for the Bad, and 84.78% for the Ugly quality images of NIST dataset. This comparison of proposed hybrid algorithm with the existing technique adapted by Jinal and Singal [21] is presented in Table 3. The graphical illustration of this comparison is also presented in Fig. 3.

Table 3: Comparison based on Similarity Score.

	Proposed Hybrid CS & PSO Algorithm	Jindal and Singla [21]
Good	95.98%	94.50%
Bad	88.43%	86.22%
Ugly	86.02%	84.78%

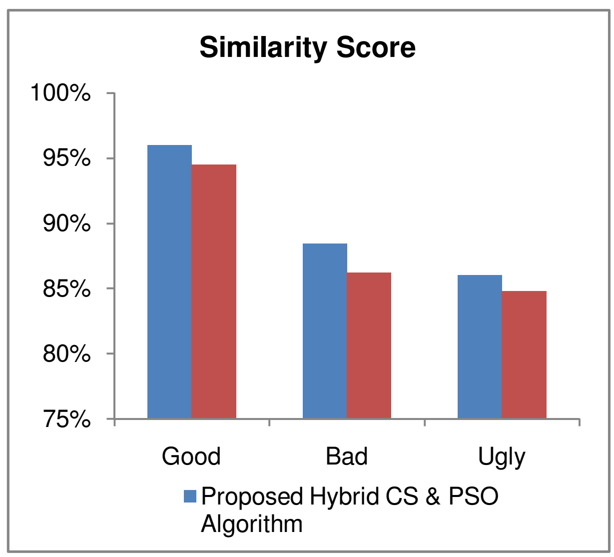


Fig. 3. Graphical Illustration of Comparison based on Similarity Score.

The results and comparison of the proposed hybrid technique with the existing technique used by Jindal and Singla [21] clearly demonstrate the dominance of the proposed hybrid CS & PSO algorithm.

To further validate the system, the proposed hybrid CS & PSO algorithm is also compared on the basis of the identification rate. The proposed hybrid CS & PSO algorithm has attained the identification rate of 98.86% for the good quality images, 90.58% for the bad quality images, and 84.70% for the ugly quality images. The comparison of the proposed hybrid technique is conducted with the techniques used by [21, 24-29]. The authors Jindal and Singla [21] have used the CS algorithm, Gu *et al*., [24] considered the non-minutiae latent fingerprint registration method, Venkatesh *et al*., [25] adapted the adaptive neuro-fuzzy inference system, Xu *et al*., [26] utilized the Embedded self learning segmentation approach, Krish *et al*., [27] have used the Minutiae generated orientation fields approach, Paulino *et al*., [28] employed the Descriptor based Hough Transform technique, and Yoon *et al.,* [29] used the Lights Out fingerprint Identification system for the recognition of latent fingerprints. The results evaluated by these authors based on the identification rate are illustrated in Table 4. Further, the graphical illustration of the comparison of the proposed hybrid CS & PSO algorithm with existing techniques is depicted in Fig. 4, Fig. 5 and 6 for the good, bad, and ugly quality images of latent fingerprints.

Table 4: Identification Rate of Proposed Hybrid Technique and Existing Techniques.

	Good	Bad	Ugly
Proposed Hybrid CS & PSO Algorithm	98.86%	90.58%	84.70%
Jindal and Singla [21]	97.72%	87.05%	83.52%
Gu *et al.,* [24]	88.97 %	84.73 %	80.83 %
Venkatesh *et al.,* [25]	92.6%	58.5%	55.6%
Xu *et al.,* [26]	71.6%	63.83%	60.89%
Krish *et al.,* [27]	95%	80%	60%
Paulino *et al.,* [28]	81.4%	67%	39%
Yoon *et al.,* [29]	78.82%	67.04%	27.05%

In Fig. 4, the performance comparison for the good quality images is conducted by considering the proposed hybrid CS & PSO algorithm and existing techniques on the basis of the identification rate parameter. The comparison results indicate the better performance of the proposed algorithm as compared to existing techniques. Among the existing techniques, Xu *et al.,* [26] lack the system with a minimum identification rate of 71.6%.

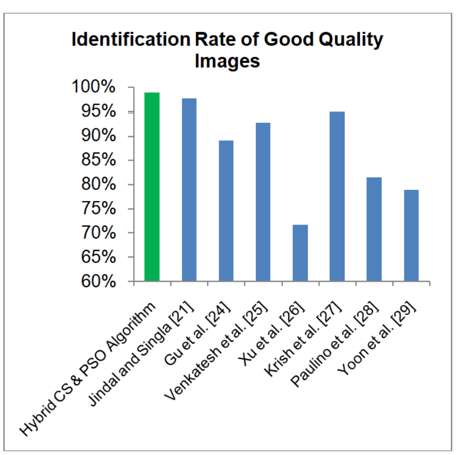


Fig. 4. Performance Comparison based on Identification Rate of Good Quality Images.

Further, Fig. 5 describes the performance comparison for the bad quality images. The comparison results clearly depict the better performance of the proposed algorithm as compared to existing techniques. Among the considered existing techniques, the technique adapted by Venkatesh *et al.,* [25] lacks the system with 58.5% identification rate.

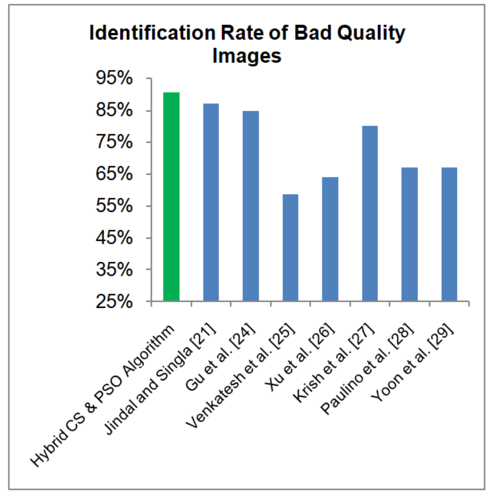


Fig. 5. Performance Comparison based on Identification Rate of Bad Quality Images.

Furthermore, the Fig. 6 presented the comparison for the ugly quality images of NIST SD-27 dataset. The comparison of proposed hybrid CS & PSO algorithm with existing techniques also indicate the dominance results of the proposed hybrid algorithm than the existing techniques. The technique utilized by Yoon *et al*., [29] lacks among other techniques with 27.05% identification rate.

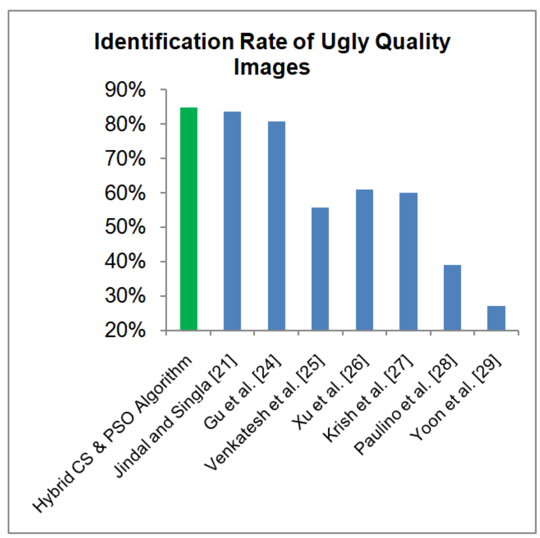


Fig. 6. Performance Comparison based on Identification Rate of Ugly Quality Images.

The overall results illustrate the outperformed performance of the proposed hybrid CS & PSO algorithm in comparison with existing techniques considered to determine the match for the latent fingerprints.

V. CONCLUSION

The paper proposed the swarm intelligence based hybrid algorithm for the recognition of latent fingerprints. The swarm intelligence based algorithms of cuckoo search and particle swarm optimization are hybridized to determine the accurate match for latent fingerprints. The experimentation is conducted on the latent fingerprints based NIST SD27 database which contains images of three different qualities as ugly, bad, and good quality. The proposed hybrid algorithm evaluates the appropriate match based on the selected minutiae features after the enhancement of fingerprint images with selected region of interest. The hybrid algorithm adapts the attributes of CS to determine the latent fingerprint match and PSO algorithm to overall attain the optimized solution. The integrated approach has attained the outperformed performance results in comparison with existing techniques on the basis of the identification rate which is evaluated based on the similarity score. The hybrid algorithm also noted with the appropriate minutiae match to determine the match for the latent fingerprints.

VI. FUTURE SCOPE

The proposed hybrid methodology can be utilized for the optimization of different research solutions such as facial expressions recognition, satellite image optimization, data optimization, etc. The current research work can also be extended with the addition of fuzzy logic to handle the fuzzy values of latent fingerprints as a future direction.

Conflict of Interest. There is no conflict of interest for this research work.

REFERENCES

[1]. Jain, A. K., Ross, A., & Pankanti, S. (2006). Biometrics: A Tool for Information Security. *IEEE Transactions on Information Forensics and Security*, *1*(2): 125-143.

[2]. Hawthorne, M. (2008). *Fingerprints: Analysis and Understanding*. CRC Press.

[3]. Xu, M., Feng, J., Lu, J., & Zhou, J. (2017). Latent Fingerprint Enhancement using Gabor and Minutia Dictionaries. In *2017 IEEE International Conference on Image Processing (ICIP)*, 3540-3544.

[4]. Makhija, S., Khatwani, A., & Roja, M. M. (2017). Performance Analysis of Latent Fingerprint Enhancement Techniques. In *2017 International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*, 96-100.

[5]. Li, J., Feng, J., & Kuo, C. C. J. (2018). Deep Convolutional Neural Network for latent Fingerprint Enhancement. *Signal Processing: Image Communication*, *60*: 52-63.

[6]. Joshi, I., Anand, A., Vatsa, M., Singh, R., Roy, S. D., & Kalra, P. (2019). Latent Fingerprint Enhancement using Generative Adversarial Networks. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 895-903.

[7]. Liu, M., Chen, X., & Wang, X. (2014). Latent Fingerprint Enhancement via Multi-Scale Patch based Sparse Representation. *IEEE Transactions on Information Forensics and Security*, *10*(1): 6-15.

[8]. Awasthi, A., Singh, A., & Yadav, P. (2015). Enhancement of Dynamic Stability using PSOMBPSS. *International Journal of Electrical, Electronics and Computer Engineering*, *4*(1): 82-88.

[9]. Singh, A., Banafar, H., & Pippal, R. S. (2015). Intrusion Detection on KDD99cup Dataset using K-means, PSO and GA: A Review. *International Journal of Electrical, Electronics and Computer Engineering*, *4*(1): 40-46.

[10]. Singh, R., and Brar, G.S. (2020). Optimized Locations for Biomass Power Plants using Ant Lion Optimizer in District Bathinda, Punjab, India. *International Journal on Emerging Technologies, 11*(1): 469-475.

[11]. Sudha, R., and Indirani, G., (2020). Fog Enabled Cloud based Intelligent Resource Management Approach using Improved Dynamical Particle Swarm Optimization model for Smart Home IoT Devices. *International Journal on Emerging Technologies*, *11*(2): 19-24.

[12]. Yang, X. S., & Deb, S. (2014). Cuckoo Search: Recent Advances and Applications. *Neural Computing and Applications*, *24*(1): 169-174.

[13]. Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks*, 4, 1942-1948.

[14]. Karar, A., & Kaur, A. (2015). Latent Fingerprint Recognition and Categorization using Multiphase Watershed Segmentation. In *2015 Annual IEEE India Conference (INDICON)*, 1-6.

[15]. Medina-Pérez, M. A., Moreno, A. M., Ballester, M. Á. F., García-Borroto, M., Loyola-González, O., & Altamirano-Robles, L. (2016). Latent Fingerprint Identification using Deformable Minutiae Clustering. *Neurocomputing*, *175*: 851-865.

[16]. Silpamol, K. V., & Thulasidharan, P. P. (2017). Detection and Rectification of Distorted Fingerprints. In *2017 International Conference on Intelligent Computing and Control (I2C2)*, 1-7.

[17]. Aravindan, A., & Anzar, S. M. (2017). Robust Partial Fingerprint Recognition using Wavelet SIFT Descriptors. *Pattern Analysis and Applications*, *20*(4): 963-979.

[18]. Cao, K., & Jain, A. K. (2018). Latent Fingerprint Recognition: Role of Texture Template. In *2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS)*, 1-9.

[19]. Venkatesh, R., Maheswari, N. U., & Jeyanthi, S. (2018). Multiple Criteria Decision Analysis Based Overlapped Latent Fingerprint Recognition System Using Fuzzy Sets. *International Journal of Fuzzy Systems*, *20*(6): 2016-2042.

[20]. Ezeobiejesi, J., & Bhanu, B. (2018). Patch based Latent Fingerprint Matching using Deep Learning. In *2018 25th IEEE International Conference on Image Processing (ICIP)*, 2017-2021.

[21]. Jindal, R., & Singla, S. (2018). An Optimised Latent Fingerprint Matching System Using Cuckoo Search. *International Journal of Intelligence Engineering & Systems*, *11*(5): 11-20.

[22]. Pavithra, R., & Suresh, K. V. (2019). Fingerprint Image Identification for Crime Detection. In *2019 International Conference on Communication and Signal Processing (ICCSP)*, 797-800.

[23]. Garris, M. D., & McCabe, R. M. (2000). Fingerprint Minutiae from Latent and Matching Tenprint Images. In *Tenprint Images. National Institute of Standards and Technology*. Gaithersburg, MD, USA, 2010.
[24]. Gu, S., Feng, J., Lu, J., & Zhou, J. (2020). Latent Fingerprint Registration via Matching Densely Sampled Points. *arXiv preprint arXiv:2005.05878*.
[25]. Venkatesh, R., Maheswari, N. U., & Jeyanthi, S. (2018). Multiple Criteria Decision Analysis Based Overlapped Latent Fingerprint Recognition System Using Fuzzy Sets. *International Journal of Fuzzy Systems*, *20*(6): 2016-2042.
[26]. Xu, J., Hu, J., & Jia, X. (2014). A Fully Automated Latent Fingerprint Matcher with Embedded Self-Learning Segmentation Module. *CoRR, volume = abs/1406.6854*.
[27]. Krish, R. P., Fierrez, J., Ramos, D., Ortega-Garcia, J., & Bigun, J. (2014). Partial Fingerprint Registration for Forensics using Minutiae-Generated Orientation Fields. In *2nd International Workshop on Biometrics and Forensics,* 1-6.
[28]. Paulino, A. A., Feng, J., & Jain, A. K. (2012). Latent Fingerprint Matching using Descriptor-based Hough Transform. *IEEE Transactions on Information Forensics and Security*, *8*(1): 31-45.
[29]. Yoon, S., Feng, J., & Jain, A. K. (2010). On Latent Fingerprint Enhancement. In *Biometric Technology for Human Identification VII* (Vol. 7667, p. 766707). International Society for Optics and Photonics.

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