IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 40, No. 1, February, 2023, pp. 375-381
Journal homepage: http://iieta.org/journals/ts

Biometric User Authentication System via Fingerprints Using Novel Hybrid Optimization Tuned Deep Learning Strategy

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https://doi.org/10.18280/ts.400138

Received: 10 October 2022
Accepted: 7 February 2023

Keywords:
biometric authentication, spotted hyena optimization minutiae matching, minutiae score evaluation

ABSTRACT

Due to security concerns, the necessity for authentication and identity techniques has increased in the modern world. A novel Accurate and Automated Fingerprint Biometric Authentication Model (AAFBAM) is introduced. The operation of the suggested AAFBAM is divided into two parts: (a) enrollment and (b) verification. During the enrollment phase, the database is prepared, and the input fingerprint is authenticated during the identification phase. The enrollment phase includes the data acquisition stage, preprocessing feature extraction stage, and minutiae point detection phase. The minutiae point detection is performed using the MISHO-based Optimized Deep Neural Network (MISHO-DNN) classifier. The weight function of DNN is tuned optimally using the proposed Memory Integrated Spotted Hyena Optimization (MISHO) algorithm to enhance its detection accuracy. The Verification Phase includes the preprocessing, feature extraction stage, minutiae point detection with MISHO-DNN, minutia matching, and minutiae score evaluation. Here, the minutiae score is obtained by matching minutiae from both phases and is compared with the threshold value. When the minutiae score exceeds the threshold, the user is identified as the genuine user, and their request is accepted. Otherwise, the user is recognized as an unauthenticated user, and their request is rejected. Finally, a comparative evaluation is conducted to validate the efficiency of the projected model.

1. INTRODUCTION

The rapid advancement of information technology has aided not only the expansion of businesses but has also been used to dismantle those same enterprises in terms of information leakage. The organization also must ensure the data's integrity. There are a variety of authentication methods accessible, each with its own set of benefits. Fingerprints are biometrics that does not alter with aging or other factors. The other characteristics of biometrics are prone to alter as a result of the age factor and other factors. As a result, fingerprint authentication may be done quickly and efficiently [1, 2]. Preprocessing, feature extraction, and classification procedures make up a fingerprint recognition system. The system should be built to prevent limits on fingerprint location, matching rate, and accuracy, all of which might be crucial sources for identifying people. Preprocessing is a technique for enhancing images to obtain high-quality images [3, 4]. The image was enhanced using techniques, such as normalization, image orientation, and Gabor filtering. The noise in the image is filtered using histogram equalization [5]. Prasad et al. [6] suggests the wavelet transform as a suitable improvement approach without providing any proof or comparable outcomes. Galton points, also known as minutiae, have been utilized to identify and classify fingerprints [7]. Despite the Euclidean distance classification, normalization, and Gabor filter performance [8] only delivered 89.6% efficiency due to a poor preprocessing strategy. One of the finest methodologies for classification that is recommended is Euclidean distance. The minutiae points and Euclidean distance categorization produce a high level of accuracy. For Euclidean distance classification, the extraction of minutiae is critical. In the chain coding approach, image quality is important for binary images [9]. When compared to pattern-based matching, minutiae-based matching is determined to be superior because just the relative location is required. Pattern-based matching, on the other hand, collects the fingerprint's overall features [10]. As a result, minutiae-based matching [11] is concerned with high precision. Furthermore, as compared to deterministic and probabilistic-based fusions, the employment of evolutionary-based fusion in multi-biometric systems is a promising state-of-the-art strategy that has demonstrated its capacity to improve performance accuracy [12]. Swarm Intelligence (SI) based hybrid meta-heuristic algorithm [13] has been used to resolve the issue of low accuracy by optimizing weights associated with hand-based modalities.

1.1 Challenges

- To achieve higher recognition performance, a multimodal biometrics recognition strategy was proposed by Basha et al. [14] using local fusion visual features and a variation Bayesian extreme learning machine. However, the rate of recognition was insufficient.
- A joint scarcity-based feature level fusion approach was developed to improve multimodal biometric identification accuracy [15]. The fusion method was stable and improved overall recognition accuracy substantially. The temporal complexity of recognition, on the other hand, was higher.
- With the help of an SVM classifier and adaptive neuron-fuzzy inference system (ANFIS), an efficient biometric multimodal recognition strategy employing Fingerprint and Iris was described by Bailey et al. [16]. The recognition rate of this approach is higher. True positive rate of person recognition, on the other hand, was insufficient.
- An ideal weight score is determined to fuse the derived feature sets of finger knuckle and finger vein images, resulting in a multimodal biometric recognition system employing finger knuckle and finger vein images [17]. As a result, recognition accuracy improves.
- The user identification and authentication utilizing multi-modal behavioral biometrics performed well in terms of false acceptance and rejection rates. However, the system's recognition accuracy was insufficient.

The key contribution of this research work is manifested below:

- To develop an accurate and automated fingerprint biometric authentication with the assistance acquired from the new MISHO based Optimized Deep neural network (MISHO-DNN) classifier.
- The weight function of DNN is optimized via Memory Integrated Spotted Hyena Optimization (MISHO) algorithm to enhance the detection accuracy. This MISHO is developed by amalgamating the concepts of SHO and CSA, respectively.

The rest of this paper is arranged as: Section 2 portrays the information regarding the proposed biometric user authentication system: an overview, Section 3 and Section 4 depict about Enrollment phase and verification phase, respectively. The results acquired with the projected model are discussed comprehensively in Section 5. This paper is concluded in Section 6.

2. DESIGN OF BIOMETRIC USER AUTHENTICATION SYSTEM

2.1 Architectural description

The proposed AAFBAM includes two major phases: (a) the enrollment phase and (b) the verification phase. Figure 1 manifests the architecture of the projected model. The steps followed in each of the phases are manifested below.

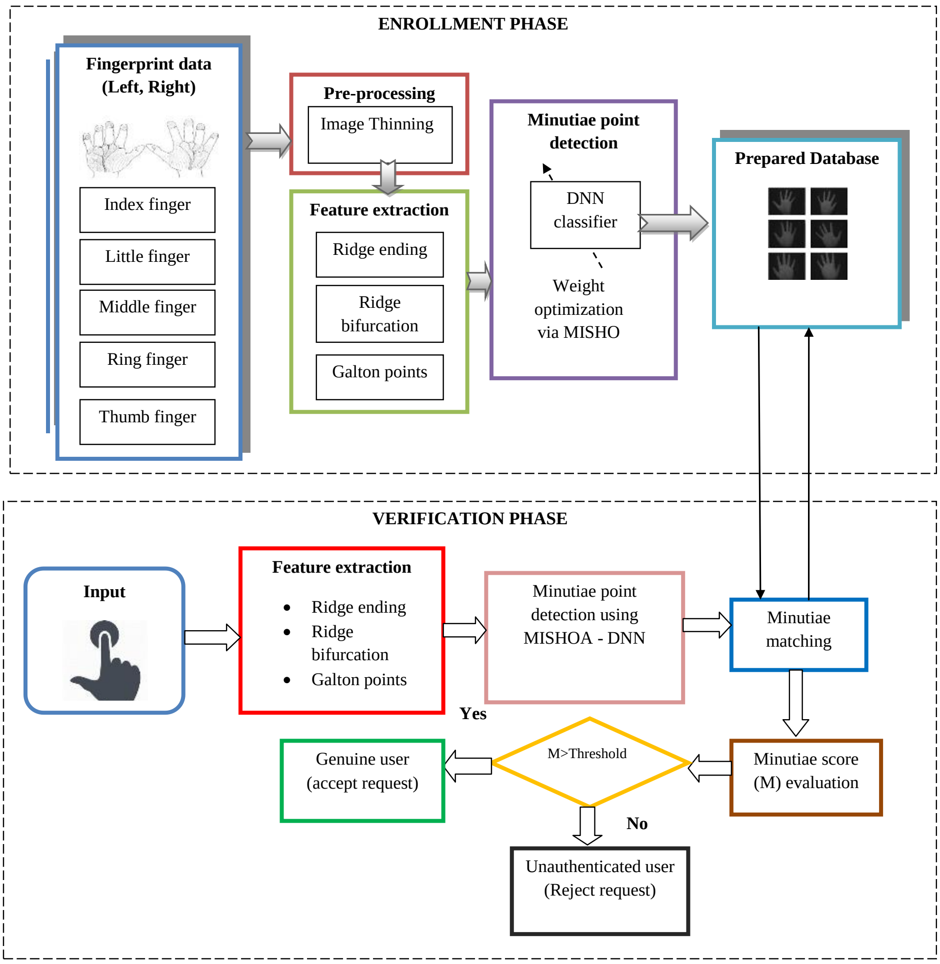

Figure 1. The architecture of the projected AAFBAM model

(a) Enrollment phase: This phase includes the "data acquisition stage, pre-processing feature extraction stage, and minutiae point detection phase". Initially, the fingerprint image H_i^{inp} from both the left and right hands is considered as the input. The collected data H_i^{inp} is pre-processed via the image thinning approach. Then, from the pre-processed images H_i^{pre}, the features, such as ridge ending f^E, Ridge bifurcation, f^B and Galton points f^G are extracted. All the features are integrated, and it is represented using the notation F. Then, the minutiae point detection is performed using the MISHO-based Optimized Deep Neural Network (MISHO-DNN) classifier [18]. To enhance the detection accuracy of the DNN (ultimate decision-maker), its weight functions W are tuned optimally using the proposed Memory Integrated Spotted Hyena Optimization (MISHO) algorithm. The proposed algorithm is developed by integrating the concepts of the SHO algorithm [19] and the CSO algorithm [20]. The prepared dataset is denoted as D_i.

(b) Verification Phase: The Verification Phase includes the "pre-processing, feature extraction stage, minutiae point detection with MISHO-DNN, minutiae matching, and minutiae score evaluation". The minutiae point is detected precisely via MISHO-DNN. The minutiae matching is accomplished between the prepared dataset D_i and the extracted features of a user's input fingerprint image. Further, the minutiae score M is computed, and it is contrasted with the pre-defined threshold value T. When the minutiae score is greater than the threshold, then the user is identified as the genuine user and the request is accepted, otherwise, the user is identified as the unauthenticated user, and the request is rejected.

3. ENROLMENT PHASE

3.1 Architectural description

This phase includes the "data acquisition stage, pre-processing, feature extraction stage, and minutiae point detection phase".

Data acquisition: The data is collected from left and right-hand fingers ("index finger, little finger, middle finger, ring finger, and thumb finger"). This image is together represented as $H_i^{inp} \in (lefthand, righthand)$.

Step 1- Pre-processing: The information quality H_i^{inp} is enhanced via the image thinning approach. The pre-processed data acquired after image thinning is denoted as H_i^{pre}.

Step 2- Feature extraction: Subsequently, H_i^{pre} the features like Ridge ending f^E, Ridge bifurcation, f^B and Galton points f^G are extracted.

Step 3- Feature fusion: All these extracted features are fused as $F = f^E + f^B + f^G$.

Minutiae point detection: Next, the minutiae point detection takes place via MISHO-DNN. To enhance the detection accuracy of DNN, its weight function W is fine-tuned using a new hybrid optimization model named as MISHO algorithm. As a result, the database is prepared effectively. The prepared dataset is denoted as D_i.

3.2 Pre-processing-image thinning

The collected input image $H_i^{inp} \in (lefthand, righthand)$ is pre-processed via image thinning to enhance the quality of H_i^{inp}. The pre-processed image acquired after image thinning is denoted as H_i^{pre}.

3.3 Feature selection

The features like Ridge ending, Ridge bifurcation, and Galton points are extracted from H_i^{pre}.These extracted features are integrated, and they are denoted as $F = f^E + f^B + f^G$.

3.4 Minute point detection

A new MISHO-DNN is used for precise minutiae point detection. To acquire a precise detection mechanism, the weight function of DNN is fine-tuned with the new MISHO model.

(a) All the inputs F_i are multiplied by their weights. The weight function W_i provides information regarding the strength of the input F_i. After the addition of weights, the bias function is added. The major objective behind this research work is to maximize the recognition accuracy R_{acc}. Mathematically, the objective function Obj can be given as per Eq. (2). To achieve this objective, the weight function W_i is fine-tuned via MISHO.

$$Z_i = F_i * W_i \tag{1}$$

$$Obj = \max(R_{acc}) \tag{2}$$

The solution fed as input to MISHO is manifested in Figure 2.

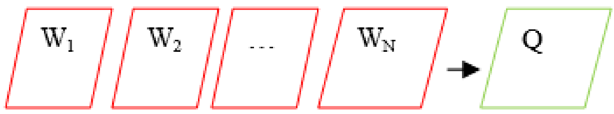

Figure 2. Solution encoding

In Figure 2, N denotes the count of weight functions.

(b) To the acquired linear expression Z_i, the activation function is applied. The activation function assists in inculcating the non-linearity in the model.

(c) All the computations are performed in the hidden layer. After the completion of the operations, the data moves to the output layer, from where the outcome is acquired.

(d) On acquiring the final prediction values from the output layer, the error is computed. The error function is the difference between the actual and the predicted outcome.

MISHO model: The stages used in the MISHO model are as follows:

Step 1: The population p of m the count of search agents is initialized. The position of the search agent is denoted as Q_i; i=1, 2, …, n. The current iteration is pointed as t and the maximal iteration count is denoted as max^t.

Step 2: Validate the termination criterion: check whether $t<max^t$. If the condition is satisfied then move to step 4, else terminate the process.

Step 3: Compute the fitness of the search agents using Eq. (2).

Step 4: Based on the computed fitness, explore the best search agent Q_{best}.

Step 5: The targeted solution (optimal weight) is encircled by the search agent in the Encircling prey phase. This phase can be modeled mathematically as per Eq. (3).

$$D = \left| B.Q_{prey}(t) - Q_{agent}(t) \right| \tag{3}$$

Here, D, Q_{prey}, and Q_{agent} points to the distance between the prey and the search agent; opposition of the prey; and position of the search agent, respectively. The next position $Q_{agent}(t+1)$ is computed as per Eq. (4). The notation B, E points to the co-efficient vector, and they are computed as per Eq. (5) and Eq. (6), respectively.

$$Q_{agent}(t+1) = Q_{prey}(t) - E.D \tag{4}$$

$$B = 2.rand1 \tag{5}$$

$$E = 2.H.rand2 - H \tag{6}$$

$$H = 5 - \left[\frac{t}{\left(5 * \max^{t}\right)} \right] \tag{7}$$

In Eq. (7), H is linearly decreasing from 5 to 0 over the variation in the iteration count.

Step 6: They search for the target solution after it has been surrounded. This phase can be mathematically given as per Eq. (8) and Eq. (9), respectively.

$$D = \left| B.Q_{best} - Q_{others} \right| \tag{8}$$

$$Q_{others} = Q_{best} - E.D \tag{9}$$

Here, Q_{best} denotes the position of the first best search agent and Q_{others} is the position of other search agents.

Step 7: In the new memory integrated attacking prey phase, the detected optimal weight (target prey) is attacked. The suggested memory-integrated prey assault phase can be analytically represented using Eq. (10) and Eq. (11), respectively.

$$Q(t+1) = \frac{C}{m} * Memory \tag{10}$$

$$Memory(t+1) = \begin{cases} Q_{agent}(t+1) & if \begin{bmatrix} fit(t+1) > \\ \quad > fit(Memory(t)) \end{bmatrix} \\ Memory(t) & \quad else \end{cases} \tag{11}$$

Here, $Q(t+1)$ save the best solution and updates the positions of other search agents according to the position of the best search agent. In addition, $Memory(t+1)$ is the memory of the next iteration. $fit(t+1)$ and $fit(Memory(t))$ is the fitness function, respectively.

Step 8: In a particular search space, verify if any search agents wander outside the border and adapt accordingly.

Step 9: If a better solution exists than that of the prior optimal solution, compute the updating search agent optimal solution and update the vector Q_{best}.

Step 10: Update the search agent fitness value for the group of spotted hyenas C.

Step 11: The algorithm will be terminated if the stopping requirement is met.

Step 12: After the stopping requirements have been met, return the most optimum solution (optimal weight) that has been achieved thus far. As a result, the database is prepared effectively. The prepared dataset is denoted as D_i.

4. VERIFICATION PHASE

4.1 Step-by-step verification process

When an I input enters the verification phase, it's validated in this phase (whether he/she is an authorized person or not).

Step 1: Initially I is pre-processed via an image thinning approach. This pre-processed image is denoted as I^{pre}. From the pre-processed data I^{pre}, the features like Ridge ending, Ridge bifurcation, and Galton points are extracted. These extracted features are together denoted as G.

Step 2: Subsequently, the minutiae point is detected via MISHO-DNN. To enhance the detection accuracy, the weight function W of DNN is fine-tuned using the new MISHO model.

Step 3: The minutias' matching is accomplished between the prepared dataset D_i and the extracted features G of I.

Step 4: Further, the minutiae score M is computed, and it is contrasted with the pre-defined threshold value T. If $M>T$, then the user is identified as the genuine user, else unauthenticated user.

5. RESULT AND DISCUSSION

5.1 Simulation procedure

The projected AAFBAM with the MISHO-DNN model has been implemented in MATLAB. The sample images and their pre-processed, as well as minutiae points identified for image sample sets, are shown in Figure 3.

5.2 Analysis on accuracy

The projected model is validated over the existing models like KNN, SVM, DNN, SHO-DNN, and CSA-DNN, respectively. The results acquired are shown in Table 1.

5.3 Analysis on F1- measure

The projected model has recorded the highest detection performance in terms of F1-measure. The results acquired are shown in Table 2.

5.4 Analysis on precision

The highest precision achievement is a major challenge faced in the existing models [12, 15]. This challenge has been overcome in this research work, and it is evident from the results shown in Table 3.

5.5 Analysis on recall

The results acquired with the existing as well as existing models in terms of recall are depicted in Table 4.

5.6 Convergence analysis

The projected model has been considered an optimization model, and it has been solved with the new MISHO model (a conceptual blend of CSA and SHO). The convergence speed is the major challenge faced by most of the existing models. The results acquired in terms of convergence speed are shown in Figure 4.

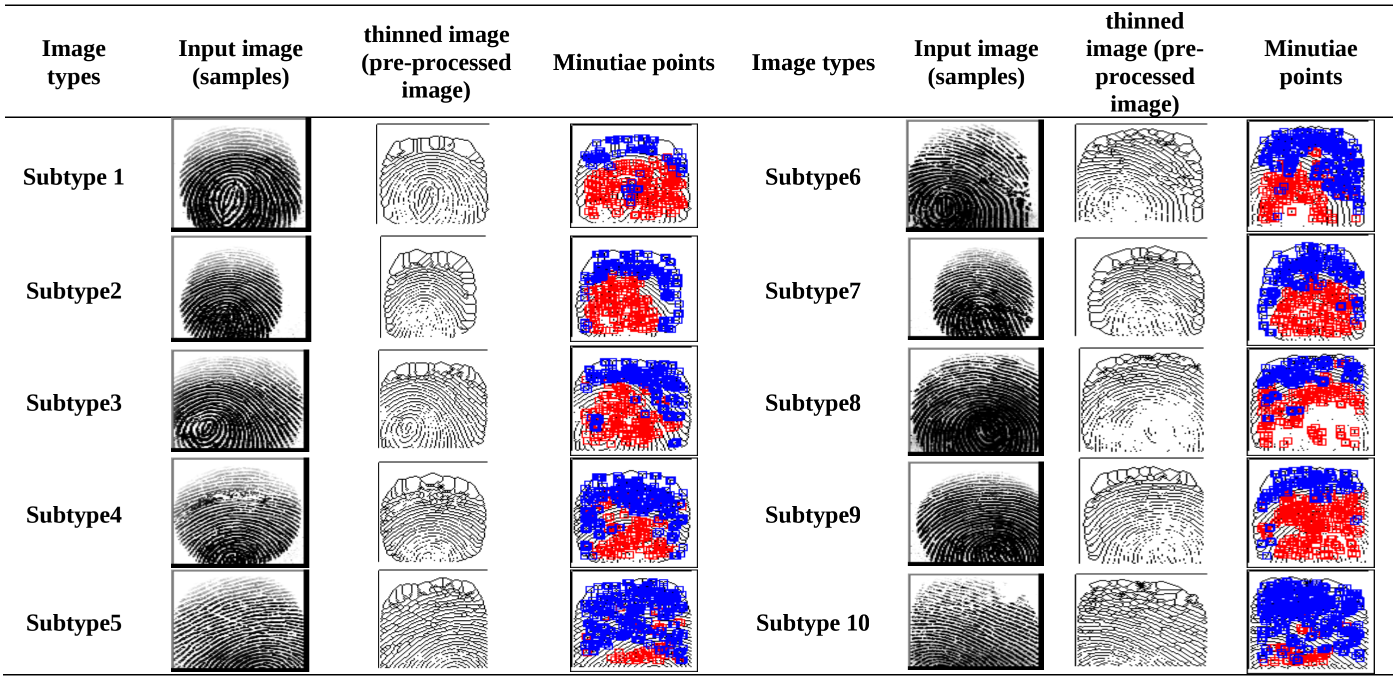

Figure 3. Sample set: Input raw image, pre-processed image, and its identified minutiae points

Table 1. Analysis of the performance of the MISHO-DNN model in terms of accuracy

Approaches	count of samples=25	count of samples=50	count of samples=75	count of samples=100	count of samples=200
KNN	85.2642005	86.14909163	84.64311055	87.1965866	90.05221628
SVM	84.78626212	82.82412277	83.75117711	86.80361492	89.33610572
DNN	85.60416026	87.83344952	84.84964197	87.9031447	91.48937378
SHO-DNN	89.33740869	88.73110533	91.94471044	89.71215596	93.19260083
CSA-DNN	86.75357192	88.05887216	91.03561308	88.6138214	92.12448169
MISHO-DNN	90.16178938	92.22771523	92.86154985	94.23333272	95.32666594

Table 2. Analysis of the performance of the MISHO-DNN model in terms of F1-measure

Approaches	count of samples=25	count of samples=50	count of samples=75	count of samples=100	count of samples=200
KNN	84.34809	83.88146	85.01988	90.33565	87.2165
SVM	81.98961	82.16496	83.31485	89.46556	87.10648
DNN	86.07264	86.50961	85.14287	92.63749	92.39413
SHO-DNN	87.35168	90.14116	92.35454	94.34025	95.42417
CSA-DNN	87.00285	86.58702	91.42392	93.47351	92.5767
MISHO-DNN	90.22633	91.53329	93.627	94.93897	95.56679

Table 3. Analysis of the performance of the MISHO-DNN model in terms of precision

Approaches	count of samples=25	count of samples=50	count of samples=75	count of samples=100	count of samples=200
KNN	83.4568	84.2453	85.13595	85.22577	88.98395
SVM	82.60569	83.04662	83.22253	84.49102	85.63596
DNN	85.27343	85.80875	86.83014	86.85674	89.16552
SHO-DNN	87.94544	89.03041	89.18225	89.68425	91.45732
CSA-DNN	86.99387	87.06939	87.19151	88.15056	90.74305
MISHO-DNN	90.20692	90.22795	92.43605	92.85763	93.29297

Table 4. Analysis of the performance of the MISHO-DNN model in terms of recall

Approaches	count of samples=25	count of samples=50	count of samples=75	count of samples=100	count of samples=200
KNN	84.09872	84.45164	85.9493	87.02201	87.8676
SVM	83.21897	83.80097	84.51808	84.79386	87.19874
DNN	85.8204	86.79228	86.86541	88.22545	90.43205
SHO-DNN	89.30965	89.64757	89.81876	91.9121	93.25075
CSA-DNN	86.02746	87.9349	88.7807	91.43693	91.90141
MISHO-DNN	90.41223	90.42335	92.04691	93.66687	95.06325

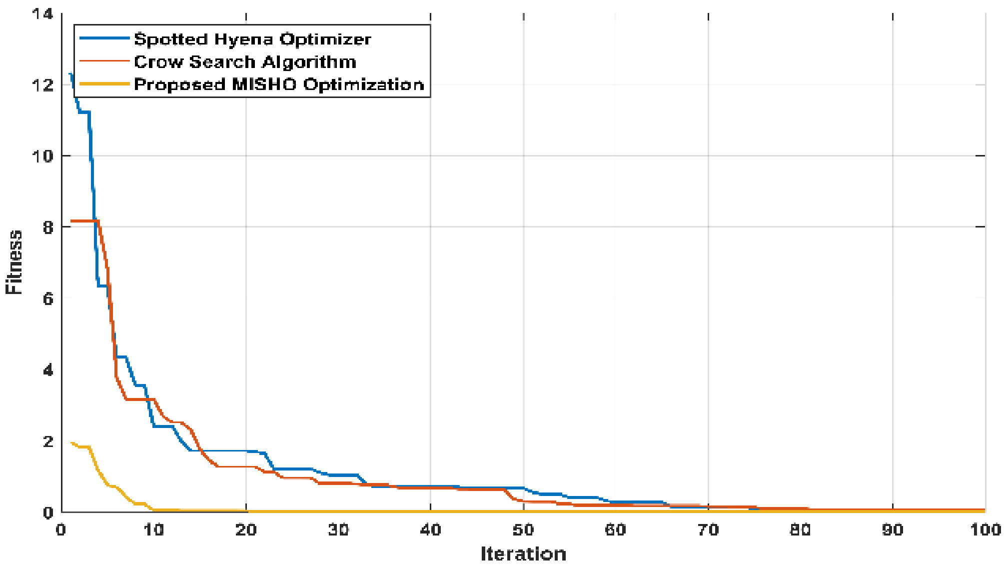

Figure 4. Convergence analysis of the projected model

6. CONCLUSION

In this research work, a novel AAFBAM has been proposed by following two major phases: (a) enrollment and (b) verification. During the enrollment phase, the database is prepared, and during the identification phase, the input fingerprint is authenticated. In the enrollment phase, the fingerprint data from both the left and right hands have been pre-processed via the image thinning approach. Then, from the pre-processed data the features, such as ridge ending, Ridge bifurcation, and Galton points have been extracted. The MISHO-DNN classifier has then used to detect Minutiae points. The suggested MISHO method was used to optimize the weight function of the RNN to improve its detection accuracy. The minutiae matching and Minutiae score evaluation, on the other hand, took place during the Verification Phase. The minutiae score is calculated by combining minutiae from both stages and comparing it to the Threshold value. If the minutiae score is above the threshold, the user is recognized as a real user, and his or her request is approved; otherwise, the person is recognized as an unauthenticated user, and his or her request has been refused. Finally, a comparative evaluation is undergone to validate the efficiency of the projected model. The projected model has recorded the highest accuracy as 95.36% while training the model with 200 counts of samples. Thus, the projected model is said to be much more significant for user authentication. In future, it's planned to test the most will huge database. Moreover, the evaluation will also be made with individuals belonging to different age groups. The hands with strains will also be taken into consideration.

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