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Comparative Analysis of Feature Selection Techniques For Fingerprint Recognition Based on Artificial Bee Colony and Teaching Learning Based Optimization

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ABSTRACT

Fingerprint biometric contains a tremendous number of textural elements which make the accurate fingerprint pattern classification challenging. Hence, an efficient algorithm for enhance recognition of fingerprint pattern is highly required. Various researches have revealed that feature selection techniques can be used to improve the discriminating ability and the computational burden of classifiers in the classification of fingerprint features. In this study, a comparative analysis of feature selection techniques for fingerprint recognition based on Artificial Bee Colony (ABC) and Teaching Learning Based Optimization (TLBO). The need to compare the performance of the two optimization techniques becomes necessary due to the fact that theoretical foundation of metaheuristic search algorithms suggested that no single algorithm is suitable for all problems. Hence, the better feature selection technique between the TLBO and ABC technique in fingerprint recognition system was investigated. Experimental result revealed that the TLBO technique outperformed the ABC technique and would produce a more reliable and accurate fingerprint authentication system.

Keywords: Fingerprint Recognition, Feature Selection, Teaching Learning Based Optimization, Artificial Bee Colony

1. INTRODUCTION

Fingerprint-based recognition has been the longest serving, most successful and popular method for person identification and it can be considered as a pattern formed on the epidermis layer of a fingertip obtained whenever the finger is pressed against any surface. The fingerprint comprises of ridges and furrows structures collectively referred to as minutiae, used as evident structural characteristics of a fingerprint which are present and different in individual fingerprints (Liu *et al.,* 2020). Emergence of low cost and compact fingerprint readers has made fingerprint modality a preferred choice in many civil and commercial applications (Jain & Kumar, 2010).

Fingerprints Recognition Systems are widely used biometric systems for authentication because of their uniqueness. The uniqueness of fingerprint means that no two people have same/identical fingerprint pattern i.e. their patterns do not change over time and unique to everyone. Even identical twins do not have identical fingerprints (Munish and Priyanka, 2018).

Feature selection is an important step used in several tasks, such as image classification, cluster analysis, data mining, pattern recognition, image retrieval, among others. It is a crucial preprocessing technique for effective data analysis, where only a subset from the original data features is chosen to eliminate noisy, irrelevant or redundant features. This task allows to reduce computational cost and improve accuracy of the data analysis process (Chen *et al.,* 2017). Many evolutionary algorithms have been used for feature selection, which include genetic algorithms and swarm algorithms. Swarm algorithms include, in turn, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Bat Algorithm (BAT), Artificial Bee Colony (ABC) and Artificial Teaching Learning Based Optimization (Karaboga and Akay, 2009; Chen *et al.,* 2017).

In this study, a comparative analysis of feature selection techniques for fingerprint recognition based on Artificial Bee Colony and Teaching Learning Based Optimization was carried out. The Teaching Learning Based Optimization (TLBO) algorithm is a nature based optimization algorithm which takes its inspiration from the natural teaching-learning phenomenon of a classroom (Rao *et al.*, 2012). Artificial Bee Colony (ABC) algorithm is a swarm-based algorithm which simulates the intelligent foraging behaviour of a honeybee swarm. Theoretical foundation of metaheuristic search algorithms suggested that no single algorithm is suitable for all problems (Wolpert and Macready, 1997; Chen *et al.*, 2018); therefore, more research is required to develop novel algorithms for different optimization problems with high efficiency (Xia *et al.*, 2017). This study reveals the better feature selection technique between the TLBO and ABC technique in fingerprint recognition system.

2. FINGERPRINT RECOGNITION

A fingerprint is seen as a set of interleaved ridges and valleys on the surface of the finger. The most popular fingerprint matching approach relies on the fact that the uniqueness of a fingerprint can be determined by minutiae, which are represented by either bifurcation or termination of ridges. The quality and enhanced minutiae, which influence recognition rates are discussed in literature (Xu and Veldhuis 2009, Mulyono and Jinn, 2008, Cappelli *et al.*, 2009). The fingerprint identification is an efficient biometric technique to authenticate human beings in real-time (Bhairannawar *et al.,* 2016). The automated fingerprint recognition system is used for both identification and verification against standard database law enforcement agencies to identify the suspect for committing crime or for attendance verification process to verify the claimed identity. The performance speed of fingerprint system is a critical factor to be addressed while dealing with large databases. The real-time processing of a fingerprint recognition system is its ability to process the large data and produce the results within certain time constraints in the order of milliseconds and sometimes microseconds depending on the application and the user requirements (Bhairannawar *et al.,* 2016).

2.1 Teaching Learning Based Optimization (TLBO)

Teaching-Learning-Based Optimization (TLBO) is a relative new algorithm proposed by Rao *et al*. (2012) motivated by the simulation of the behaviours of teaching and learning process in a classroom. TLBO utilizes two productive operators, namely, teaching phase and learning phase to search good solutions (Rao, 2016). The algorithm was found to be more efficient due to the fact that errors caused by the improper tuning of the specific parameters are removed (Aruna and Kalra, 2017). Due to its attractive characters such as simple concept, without the specific algorithm parameters, easy implementation, and rapid convergence, TLBO has captured great attention and has been extended to handle constrained, multi-objective, large-scale and dynamic optimization problems (Patel and Savsani, 2016; Keesari and Rao, 2014). Furthermore, TLBO has also been successfully applied to many scientific and engineering fields, such as neural network training, power system dispatch and production scheduling (Chen *et al.,* 2018, 2018a)

2.2 Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) algorithm is a recently proposed optimization technique which simulates the intelligent foraging behavior of honey bees. A set of honey bees is called swarm which can successfully accomplish tasks through social cooperation. In the ABC algorithm, there are three types of bees: employed bees, onlooker bees, and scout bees (Xu *et al.,* 2013). The employed bees search food around the food source in their memory; meanwhile they share the information of these food sources to the onlooker bees. The onlooker bees tend to select good food sources from those found by the employed bees. The food source that has higher quality (fitness) will have a large chance to be selected by the onlooker bees than the one of lower quality. The scout bees are translated from a few employed bees, which abandon their food sources and search new ones (Zhu and Kwong, 2010). In the ABC algorithm, the first half of the swarm consists of employed bees, and the second half constitutes the onlooker bees. The number of employed bees or the on looker bees is equal to the number of solutions in the swarm (Karaboga, 2005).

2.3 Related Works

Stephen and Reddy (2013) presented an image enhancement technique based on Teaching Learning Based Optimization to obtain reliable estimates of minutiae locations prior to minutiae extraction. The optimization technique, is then implemented to control and change the parameters in the transformation function which is applied on the poor quality fingerprint images to remove noise. The application of the technique was found to bring about improvements in Fingerprint Image Quality, Robustness Index and Verification Performance as three evaluation criterions. A comparative study between the proposed techniques with many other available models from the literature established the efficacy of the proposed enhancement techniques

Luo *et al.,* (2014) presented an efficient algorithm for fingerprint classification combining Curvelet Transform (CT) and Gray-Level Co-occurrence Matrix (GLCM). Fingerprint classification was accomplished by K-nearest neighbour classifiers. Extensive experiments were performed on 4000 images of NIST-4 database. The proposed algorithm achieves the classification accuracy of 94.6% for the five-class classification problem and 96.8% for the four-class classification problem with 1.8 percent rejection, respectively. The experimental results verified that proposed algorithm has higher recognition rate than that of wavelet-based techniques.

Sasikala and Lakshmi (2015) developed a new and efficient fingerprint classification approach based on Artificial Bee Colony with fuzzy based neural network techniques to overcome the limitations associated with some existing classification approaches. Their work used efficient min-max normalization and median filtering for pre-processing, and multiple static features were extracted from Gabor filtering. Then, from the multiple static features obtained from 2D Gabor filtering, best features were selected using Artificial Bee Colony (ABC) optimization based on its searching capability. This optimization based feature selection selects only the optimal set of features which was used for classification. The experimental result revealed that the involvement of ABC lessens the complexity and the time taken by the classifier. Also, the proposed work showed better results in terms of sensitivity, precision, specificity and classification accuracy.

3. METHODOLOGY

In this study, comparative assessment of the performance of TLBO and ABC used as feature selection techniques in fingerprint recognition was carried out. The required stages involved in developing fingerprint recognition system are highlighted as follows:

Stage 1: Fingerprint Image Acquisition
Stage 2: Fingerprint Image Pre-processing
Stage 3: Feature Extraction Based on Kernel Principal Component Analysis
Stage 4: Feature Selection Based on either TLBO or ABC
Stage 5: Classification using SVM
Stage 6: Results Evaluation.

Figure1 illustrates the scheme of the study using the two feature selection techniques for fingerprint recognition.

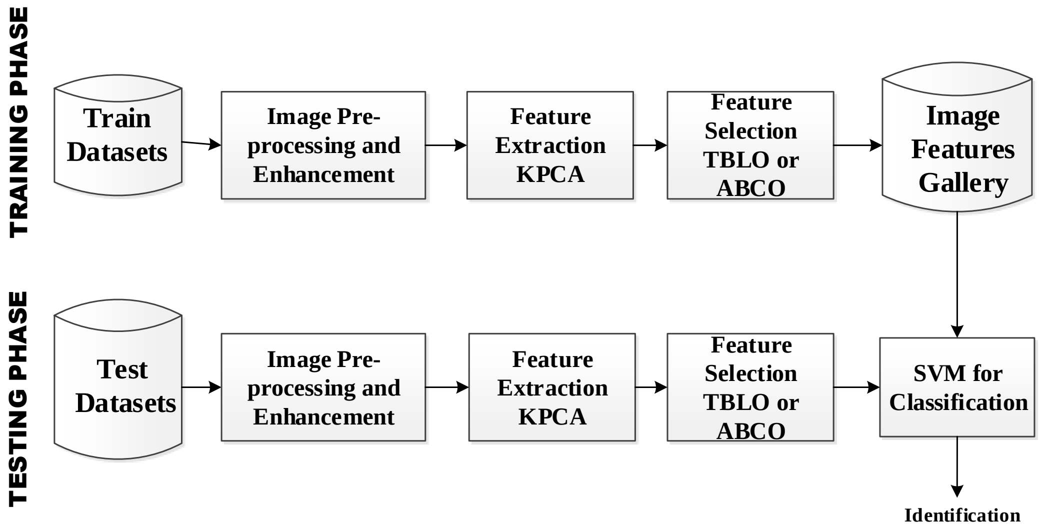

Figure 1: Scheme of the study

3.1 Acquisition of Fingerprint Images

Fingerprint images of 40 subjects with 10 different fingerprint samples for left and right hand were captured with a fingerprint scanner in 700 by 800 pixels. The original fingerprint images were downsized into 200 by 200 pixels without any alteration in the images. The database was populated with 800 images, that is, 400 images for left fingerprints and 400 images for right fingerprints. Out of the entire images collected; 500 images were used for training the system while 300 images were used for testing.

3.2 Image pre-processing

The preprocessing stage involved conversion to grayscale and enhancement of image by using Histogram Equalization after applying this enhancement algorithm a contrast image was obtained. This removes noise and other unwanted element from the fingerprint images.

The images that was acquired from the fingerprint scanner are coloured in three-dimensional form (3-D) and required to be converted into grayscale (two-dimensional form (2-D)) with pixel values between 0 and 255, that is, image in black and white. Each of the grayscale images was expressed and stored in form of matrix in MATLAB which was converted to vector image for further processes. Histogram Equalization was the first step used for the image enhancement process. It is a technique for adjusting the pixel intensities of image to enhance the contrast. Through this adjustment the intensities were better distributed on the histogram.

3.3 Feature Extraction

Kernel Principal Component Analysis (KPCA) was employed in this study to extract features and reduces the dimension sizes of images to form Eigen fingerprints. The resultant feature representation offered a suitable platform for selecting the optimal feature subsets. In constructing kernel PCA, assuming there is a nonlinear transformation $\emptyset(x)$ from the original D-dimensional feature space to an M-dimensional feature space, where usually$M \gg D$. Then each data point x_i is projected to a point $\emptyset(x_i)$. The steps for the KPCA algorithm are as follow:

Step 1: The projected new features are equated to zero mean as thus:

$$\frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i) = 0 \quad (1)$$

Step 2: The covariance matrix of the projected features is M x M, calculated by

$$C = \frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i)\emptyset(x_i)^{T}=0 \quad (2)$$

Step 3: Compute eigenvalues and eigenvectors as given by equation 3

$$Cv_k = \lambda_k v_k \quad 3$$

where k= 1,2, . . . M. from Equation (2) and (3): Equation (4) is derived as thus;

$$\frac{1}{N}\sum_{i=1}^{N} \emptyset(x_i)\{\emptyset(x_i)^{\mathrm{T}} v_k\} = \lambda_k v_k \quad 4$$

and this can be rewritten as $v_k = \sum_{i=1}^{N} a_{ki}\emptyset(x_i)$. 5

Now by substituting v_k in Equation (4) with Equation (5), it gives

$$\frac{1}{N}\sum_{i=1}^{N} \emptyset(x_i)\emptyset(x_i)^{\mathrm{T}} \sum_{i=1}^{N} a_{kj}\emptyset(x_j) = \lambda_{k\sum_{i=1}^{N} a_{ki}\emptyset(x_i)}. \quad 6$$

If the kernel function is then defined as $k(x_{i,}x_j) = \emptyset(x_i)^{\mathrm{T}}\emptyset(x_j)$, 7

and multiply both sides of Equation (7) by $\emptyset(x_l)^{\mathrm{T}}$ to have

$$\frac{1}{N}\sum_{i=1}^{N} k(x_{l,}\, x_i) \sum_{j=1}^{N} a_{kj}\, k(x_{l,}\, x_j) = \lambda_{k\sum_{i=1}^{N} a\, ki}\, k(x_{l\,,} x_i). \quad 8$$

Step 4: Construct the kernel matrix K from the data set $\{x_i\}$ using Equation (10) By using matrix notation

$$K^2 a_k = \lambda_k N K a_k \quad 9$$

where $K_{i,j} = k(x_{i\,,} x_j)$, 10

and $a_k$is the N-dimensional column vector of a_{ki}

$$a_k = [\, a_{k1}, a_{k2,} \; \ldots \; a_{kN}]^{\mathrm{T}} \quad 11$$

a_k can be solved by $Ka_k = \lambda_k N a_k$ 12

and the resulting kernel principal components can be calculated by using

Step 5: Compute the kernel principal components $y_k(x)$ using Equation (13)

$$y_k(x) = \emptyset(x)^{\mathrm{T}} v_k = \sum_{i=1}^{N} a_{ki} k(x, x_i) \quad 13$$

Step 6: Compute the Gram matrix $\breve{K}$ using Equation (3.14) if the projected dataset $\{\emptyset(x_i)\}$ does not have zero mean, Gram matrix $\breve{K}$can be used to substitute the kernel matrix K. The Gram matrix is given by $\breve{K} = K - 1_N K - K 1_N + 1_N K 1_N$ 14

where 1_N is the N x N matrix with all elements equal to $\frac{1}{N}$.

3.5 Feature Selection

The feature selection techniques that was adopted at this phase are teaching learning based Optimization (TLBO) and Artificial Bee Colony Optimization (ABC). The features extracted by KPCA were presented to TLBO and ABC techniques individually for feature selection. The procedure of TLBO and ABC techniques as feature selection technique is shown in Algorithm 1 and 2 respectively.

3.6 Classification Using SVM

The Selected best global position w_i of the TLBO and ABC in each cases trained the SVM with the detected feature subset mapped by w_i and modelled with the optimized parameters C and σ using equation (3.15):

$$min \quad \frac{1}{2}\|w_i\|^2 + C\sum_{i=1}^{N} \xi_i \quad 15$$

$$\text{Such that} \quad \sum_{i=1}^{N} w_i x_i \geq \left(\frac{1-\xi_i}{y_i}\right) - b \qquad 16$$

$$i = 1, 2, \ldots, N, \qquad \xi_i \geq 0, \qquad i = 1, 2, \ldots, N,$$

Where N is the size of the training dataset and C is a positive regularization constant or cost function, which defines the trade-off between a large margin and a misclassification error w_i. The following rule was applied to obtain the final classification of each instance:

$$y_i = \arg\max_{k(1...k)}(w_i^T y_i(x_i) + b_i) \qquad 17$$

Each class was labelled base on classification.

Algorithm 1: TLBO for Feature Selection

Initialize *NP* (number of learners) and *D* (dimension);
Initialize learners and evaluate them;
while stopping condition is not met
  Choose the best learner as $\boldsymbol{x}_{teacher}$
  Calculate the mean $\boldsymbol{x}_{mean}$ of all learners;
  for each learner $\boldsymbol{x}_i$
    // Teacher phase //
    TF = round (1 + rand (0, 1));
    Update the learner according to Equation (3.18);

$$\boldsymbol{x}_{i,new} = \boldsymbol{x}_{i,old} + rand \cdot (\boldsymbol{x}_{teacher} - \boldsymbol{T}_F \cdot \boldsymbol{x}_{mean}) \qquad 18$$

    Evaluate the new learner $\boldsymbol{x}_{i,new}$;
    Accept $\boldsymbol{x}_i$, new if it is better than the old one $\boldsymbol{x}_{i,old}$
    // Learner phase //
    Randomly select another learner $\boldsymbol{x}_j$ which is different from $\boldsymbol{x}_i$;
    Update the learner according to equation (3.19)

$$\boldsymbol{x}_{i,new} = \begin{cases} \boldsymbol{x}_{i,old} + rand \cdot (\boldsymbol{x}_i - \boldsymbol{x}_j), & if\ f(\boldsymbol{x}_i) \leq f(\boldsymbol{x}_j), \\ \boldsymbol{x}_{i,old} + rand \cdot (\boldsymbol{x}_j - \boldsymbol{x}_i), & if\ f(\boldsymbol{x}_i) > f(\boldsymbol{x}_j), \end{cases} \qquad 19$$

    Evaluate the new learner $\boldsymbol{x}_{i,new}$;
    Accept $\boldsymbol{x}_{i,new}$ if it is better than the old one $\boldsymbol{x}_{i,old}$;
  end for
end while

3.7 Evaluation Measures

The performance of TLBO and ABC techniques on trained and recognized fingerprints images were measured using recognition accuracy, sensitivity, false positive rate and total recognition time. The following parameters were used to measure or evaluate the overall performance of the system:

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

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad 21$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad 22$$

$$\text{Recognition Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad 23$$

Algorithm 2: ABC for Feature Selection

1. Initialize the population of solutions x_{ij}, *i* = 1. . .*SN*, *j* = 1. . .*D*
2. Evaluate the population
3. cycle=1
4. **repeat**
5. Produce new solutions v_{ij} for the employed bees by using (2) and evaluate them

$$\boldsymbol{v}_{ij} = x_{ij} + \emptyset_{ij}(\boldsymbol{x}_{ij} - \boldsymbol{x}_{kj}) \quad (2)$$

6. Apply the greedy selection process
7. Calculate the probability values p_{ij} for the solutions x_{ij} by (1)

$$\boldsymbol{p}_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (1)$$

8. Produce the new solutions v_{ij} for the onlookers from the solutions x_{ij} selected depending on p_{ij} and evaluate them
9. Apply the greedy selection process
10. Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_{ij} by (3)

$$x_i^j = x_{min}^j + rand\ (0,1)(x_{max}^j - x_{min}^j) \quad (3)$$

11. Memorize the best solution achieved so far
12. cycle=cycle+1
13. **until** cycle= maximum cycle number

3.8 Implementation

MATLAB R2018 on Windows 10 64-bit operating system, Intel®Core™ i5-2540M CPU@2.60GHz Central Processing Unit, 6GB Random Access Memory and 500GB hard disk drive was used to implement the proposed work. An interactive Graphic User Interface (GUI) was developed with a real time database. Figure 3.2 depicts the GUI application for the proposed work.

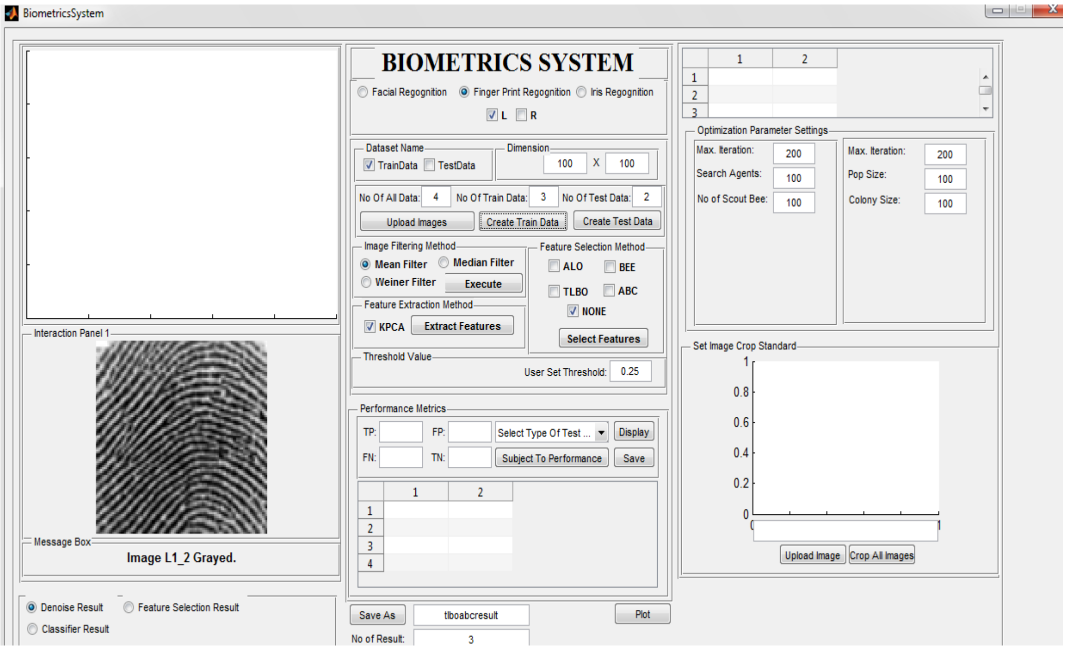

Figure 2: Graphic User Interface showing the training and testing phase

4.0 Result and Discussion

The result obtainable in Table 1 shows the contingency table for the performance of TLBO and ABC technique.

Table 1: Contingency table for the performance of TLBO and ABC technique

		TBLO		ABC	
		Predicted Class		Predicted Class	
		Positive	Negative	Positive	Negative
Actual	Postive (100)	97 (TP)	3 (FN)	94 (TP)	6 (FN)
Class	Negative	2 (FP)	48 (TN)	3 (TP)	47 (TN)

The fingerprint test dataset comprises of 150 datasets out of which 100 were genuine and 50 were false. From Table 4.1 with TLBO technique, 97 fingerprint dataset were classified correctly as genuine while 3 fingerprint datasets were misclassified as false. Also, 48 false fingerprint dataset were correctly classified as false while 2 were wrongly classified as genuine. Similarly, from Table 1 with ABC technique, 94 fingerprint dataset were classified correctly as genuine while 6 fingerprint datasets were misclassified as false. Also, 47 false fingerprint dataset were correctly classified as false while 3 were wrongly classified as genuine.

Table 2: Performance of TLBO and ABC Technique

Feature Selection Technique	Accuracy (%)	Sensitivity (%)	FPR (%)	Computation Time (s)

TLBO	96.67	97.00	4.00	58.65
ABC	94.00	94.00	6.00	67.98

Also, Table 2 presents the results obtained by the TLBO and ABC technique with respect to the performance metrics. The table revealed that TLBO achieved a false positive rate of 4.00%, sensitivity of 97.00% and accuracy of 96.67% at 58.65 seconds. Moreover, the ABC technique achieved a false positive rate of 6.00%, sensitivity of 94.00% and accuracy of 94.00% at 67.98 seconds. The result presented revealed that TLBO outperformed ABC technique as feature selection technique in fingerprint recognition. The TLBO technique brings about a more discriminant features in the identification of fingerprint. The result achieved in this study is in line with the works of (Stephen and Reddy, 2013; Aruna and Kalra, 2017) which stated that TLBO outperformed some common metaheuristic techniques.

The paired t-test analysis conducted between the recognition accuracy of TLBO and ABC technique revealed that there is significant distinction in the test resulst; having a mean difference ($\mu = 2.5$). Nevertheless, the result confirmed significant difference at $P < 0.01; P = 0.001$ with $t\ value = 14.94$. Test of significance of the recognition accuracy evaluated at 95% confidence level showed that there was significant difference between the TLBO and ABC technique. The t-test result validated the fact that the TLBO technique is more accurate than ABC.

5. CONCLUSION

The results achieved in this study have proven the fact that TLBO outperformed the ABC technique in fingerprint recognition. Hence, TLBO technique will be a better feature selection technique than ABC and would produce a more reliable accurate fingerprint authentication system.

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