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Optimized Negative Selection Algorithm for Image Classification in Multimodal Biometric System

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Abstract

Classification is a crucial stage in identification systems, most specifically in biometric identification systems. A weak and inaccurate classification system may produce false identity, which in turn impacts negatively on delicate decisions. Decision making in biometric systems is done at the classification stage. Due to the importance of this stage, many classifiers have been developed and modified by researchers. However, most of the existing classifiers are limited in accuracy due to false representation of image features, improper training of classifier models for newly emerging data (over-fitting or under-fitting problem) and lack of an efficient mode of generating model parameters (scalability problem). The Negative Selection Algorithm (NSA) is one of the major algorithms of the Artificial Immune System, inspired by the operation of the mammalian immune system for solving classification problems. However, it is still prone to the inability to consider the whole self-space during the detectors/features generation process. Hence, this work developed an Optimized Negative Selection Algorithm (ONSA) for image classification in biometric systems. The ONSA is characterized by the ability to consider whole feature spaces (feature selection balance), having good training capability and low scalability problems. The performance of the ONSA was compared with that of the standard NSA (SNSA), and it was discovered that the ONSA has greater recognition accuracy by producing 98.33% accuracy compared with that of the SNSA which is 96.33%. The ONSA produced TP and TN values of 146% and 149%, respectively, while the SNSA produced 143% and 146% for TP and TN, respectively. Also, the ONSA generated a lower FN and FP rate of 4.00% and 1.00%, respectively, compared to the SNSA, which generated FN and FP values of 7.00% and 4.00%, respectively. Therefore, it was discovered in this work that global feature selection improves recognition accuracy in biometric systems. The developed biometric system can be adapted by any organization that requires an ultra-secure identification system.

Keywords

Artificial immune system; Negative selection algorithm; Optimized negative selection algorithm; Teaching-learning-based optimization algorithm; Recognition accuracy; NSA.

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1 Introduction

Identity is a characteristic that determines who or what a person or thing is. It is used to distinguish the character or personality of an individual. The first thing needed while creating identity is information gathering. The information gathered can then be used to create a classification pattern based on some pre-set criteria. Image classification is a crucial and essential stage in biometric systems. It is an identity creation tool that analyses images and determines the categories that the images fall under. In essence, image classification involves categorizing different data into groups that might have been pre-defined using algorithms. The ability to carry out an accurate classification depends on various factors such as data population, image processing technique, image quality, feature selection method and classification technique (Nath et al., 2014). Sanderson and Paliwal (2004) said that identity is an essential instrument that forms and designs societal collaborations. There are two ways of creating identity: the conventional way and the biometric way. The conventional ways of identification, such as a person's name, home address and identification numbers, can only be effective if they are consistent, unique, permanent and unambiguous and are bonded to the physical selves (Arun et al., 2019). Unfortunately, they are not mostly or necessarily unique. For example, Ayoola Smith can also be referred to as Smith Ayoola. It must also be permanent; for instance, Ayoola Smith nee Johnson maybe after marriage or change of name should still be seen as Ayoola Smith.

It is also complicated, if not impossible, for the conventional means of identification to be linked with the object physically. Therefore, there is a need for a biometric system which is a reliable means of identification that fulfils all the characteristics mentioned above (Arun et al., 2019). Biometrics is solely dependent on characteristics that are mostly measurable and permanent. Biometrics involves the use of human physiological and behavioural traits such as the face, fingerprint, iris, gait, voice, signature, DNA and so on for identification. Biometric systems offer enhanced security over conventional electronic access control methods, as the human body cannot be forgotten, stolen, forged or lost (Falohun et al., 2013).

A biometric system that merges more than one biometric trait is called a multimodal biometric system. Merging two or more biometric traits while designing a biometric system makes it more secure and reliable. Multibiometric consists of processing stages such as image capturing, image pre-processing, feature extraction, feature fusion, classification and decision making. This work focus on the classification stage by developing a classification algorithm called the Optimized Negative Selection Algorithm (ONSA). The ONSA was used in this research for image classification in a multimodal biometric system that fused five biometric traits, namely: face, fingerprint, iris, voice and signature. Hence, an optimized algorithm that has the following benefits has been developed in this work:

- ability to consider whole feature space (global feature selection) during feature selection stage
- better recognition accuracy
- better and proper training of a classifier model for newly emerging data (over-fitting or under-fitting problem) and
- an efficient mode of generating model parameters (scalability).

2 Literature Review

Many improvements have been carried out to improve the performance of classification algorithms. The major problem with classification algorithms is the tuning of the algorithm parameters, both specific and general. The NSA is one of the algorithms that have been used for classification and identification purposes, most specifically in intruder detection systems. However, many improvements and optimizations have been made to the traditional NSA. These improvements are mainly on the detector's generation process, and are reviewed in this section. Unimodal biometric systems, which are based on utilizing a single biometric trait, have been found to often face limitations that negatively affect their

overall performance. The limitation is due to a variety of reasons such as intra-class variability, non-universality, noisy data, low distinctiveness, spoof attacks and unacceptable errors due to the nature of the biometric trait considered. In order to solve some of the limitations of unimodal biometric systems mentioned above, multimodal biometric systems have been introduced, which involves the integration of more than one biometric trait for accurate authentication. Many researchers have worked on integrating more than one biometric trait to increase the system accuracy, and the integration of biometric features has been implemented at different stages of the biometric systems.

In Li et al. (2010), and improved negative selection algorithm called the Outlier Robust Negative Selection Algorithm (ORNSA) was proposed, which uses an outlier robust and boundary detection technology to section the selves into boundary selves, internal selves and outlier selves. In order to cover non-self-space more effectively, the positive was combined with the negative self-spaces. The significant difference between the conventional NSA and the ORNSA occurs at the detection stage, in which the reverse detector set (RD) and the mature detector set (MD) are both used during the detector generation stage. The ORNSA experimented with synthesized and benchmark users' iris data and the results of the experiment show that the ORNSA has better adaptability with better data detection performance when fewer detector sets were used. It was also confirmed that the proposed algorithm could perform well with the training of a noisy data set.

Chen et al. (2013) proposed an improved NSA called the CB-RNSA, which is based on hierarchical clustering of self-sets. The self-data are first pre-processed by hierarchical clustering and then replaced with self-cluster centres to match with the candidate detectors to reduce the distance calculation cost. In order to reduce detector redundancy, the candidate detectors were restricted to the lower coverage space during the detector generation process. Theoretical analysis of the CB-RNSA shows that its time complexity is irrelevant to the self-set size. Therefore, the exponentially high training cost in the conventional NSA is resolved. The efficiency of the detector generation under a big self-set is also increased. The experimental results show that the detector generation rate of the CB-RNSA is higher than that of the conventional NSA.

Aiqiang et al. (2011) discovered that the problem of finding a good distribution of detectors in the NSA could be better handled by optimization. They proposed a new NSA using an optimization strategy based on a re-heating simulated annealing algorithm. The algorithm modified the process of random generation of detectors to achieve optimal distribution without changing the number of detectors. An optimal distribution maximized the set of detector coverage and reduced their overlapping without covering the self-set. The proposed algorithm was tested on 2-dimensional synthetic data, and the results show that the detection rate is improved and the false alarm rate is reduced. The algorithm was also applied to fault detection in analogue circuits, and the results demonstrated that the proposed algorithm performs better than an Artificial Neural Network.

In Toh et al. (2004), a multibiometric system that combined features of speech, fingerprint and hand geometry employing global learning (GL) and local learning (LL) decision as the fusion technique was developed. The work designed two biometric systems: a unimodal of fingerprint and speech and a trimodal combination of all the three traits. The results showed that the trimodal system of LL produced an equal error rate (EER) of 0.2904% and 0.7394% for testing and training data sets, respectively. In comparison, the trimodal system of LL produced an EER of 0.1044% and 0.2165% for training and testing, respectively. The LL fusion technique was found to be the better of the two paradigms considered in this work as it produced a lower EER.

Sanches et al. (2007) proposed a multibiometric recognition system that combined three different biometrics computed from the same hand image. Features extracted from each of the five fingers' surface areas were fused at score level into a single mode. Features gotten from hand geometry, palm print, and

fingerprints of one hand were also fused at the decision level. University of Science and Technology of Hanoi image database were used, and the evaluation of results of the unimodal hand geometry produced a recognition rate (RR), false rejection rate (FRR) and false acceptance rate (FAR) of 91.65%, 4.80% and 3.55%, respectively. The unimodal of the palmprint produced 86.19%, 9.69% and 4.12% respectively. In comparison, the finger surface is 97.25%, 2.29% and 0.46% respectively. However, the multimodal of all produced RR, FRR and FAR of 96.80%, 2.90% and 0.31%, respectively. Overall, the results show that the proposed method can be improved upon and might be considered useful for high-security applications.

Kounoudes et al. (2008) designed a multimodal biometric system that combined voice, face, finger and palm features and compared the results with those of the unimodal biometrics of each of the traits. Biometric evidence was collected from 30 individuals using BOLYBIO datasets. Five data-capturing sessions were stored for each trait, four of which were used for training and one for testing. The same database is used for testing the four biometric systems developed in this work. Features were fused at the decision level in the multimodal biometric system developed. The developed systems were evaluated using FAR and FRR. The unimodal of voice produced FRR and FAR 4.11% and 4.12%, respectively, hand geometry generated 11.4% and 9.9%, and fingerprint produced 9.1% and 9.4%. Similarly, the multimodal of all the traits generated FRR and FAR of 0.86% and 1.23%, respectively. Evaluation of the results showed that even a weak single modality verification system could lead to high performance once a simple fusion technique is adopted.

Zhang et al. (2008) combined three biometric traits of face, palm print and gait. Features were selected using the Geometry Preserving Projections (GPP) algorithm. Two data arrays named YALE-HKPU-USF and FERET-HKPU-USF were built. The recognition rate obtained using Kernel GPP (KGPP) was 90.22% and 93.67 for the YALE-HKPU-USF and FERET-HKPU-USF datasets. This work achieved high recognition rates but was based on a limited data set.

Patil and Jagtap (2020) developed a system that combined finger knuckle and retina image based multimodal biometric authentication system using the IITD and STARE database. Experiments were carried out at various threshold values of 0.40, 0.45, 0.50 and 0.55. The results showed that the highest GAR rate, 98.66% and the lowest FAR of 0.33% at 0.50, gave the best system performance rate.

Aizi and Ouslim (2019) developed a multibiometric fusion method for the identification of persons using iris and fingerprints. Each modality was separately processed to generate a score vector. Features were fused at the score level. The score range was split into three zones of interest relevant to the proposed identification method. The extracted regions were fused using two approaches, namely a decision tree combined with the weighted sum (Based on Chosen Coefficient or BCC) and fuzzy logic (Based on Fuzzy Logic or BFL). The evaluation of the performance of the proposed methods was conducted using FAR, FRR, enrolee false acceptance rate (EFAR) and recognition rate (RR). The unimodal system of iris generated FRR, EFAR, FAR and RR of 10.55%, 3.89%, 7,50% and 85.56%, respectively, while those of fingerprint are 16.11%, 7.22%, 12.50% and 76.67%, respectively. However, the multimodal based on BCC achieved FRR, EFAR, FAR and RR of 3.89%, 1.11%, 1.50% and 95.00%, compared to those of BFL, which produced 5.00%, 0.56%, 2.50% and 94.44%. The obtained results illustrated that the proposed multimodal biometric system outperforms the unimodal systems. The results also indicated that the BCC fusion approach achieves slightly better performance than BFL.

Table 1. *Review summary of related works.*

Author(s) and year	Methodology	Results	Limitations
Li et al. (2010)	Proposed an improved negative selection algorithm called Outlier Robust Negative Selection Algorithm (ORNSA), which uses an outlier robust and boundary detection technology to section the selves into boundary selves, internal selves and outlier selves.	ORNSA was able to achieve 99.89% detection rate with 0% false alarm rate at both detection ratios.	The proposed technique was experimented with synthesized data set, so might not perform well on an uncontrolled data set.
Chen et al. (2013)	Proposed an improved NSA called the CB-RNSA, which is based on hierarchical clustering of self-sets. The self-data are first pre-processed by hierarchical clustering and then replaced with self-cluster centres to match with the candidate detectors.	CB-RNSA performs better than the classical NSA and v-detector algorithm by 12.3% and 7.4% respectively with a low false alarm rate of 4.9%.	The CB-RNSA is too complex with high processing time.
Aiqiang et al. (2011)	Proposed a new NSA using an optimization strategy based on a re-heating simulated annealing algorithm to modify the random detector generation.	The optimized algorithm produced 99.14% detection rate with false alarm rate of 0%.	Fewer samples were considered.
Toh et al. (2004)	Developed a multibiometric system that combined features of speech, fingerprint and hand geometry employing global learning (GL) and local learning (LL) decision as fusion techniques.	The trimodal system of LL produced an equal error rate (EER) of 0.2904% and 0.7394%, while LL produced EER of 0.1044% and 0.2165%.	The proposed system was only used for verification purposes with a 50% equal error rate.
Sanches et al. (2007)	Proposed a multibiometric recognition system that combined three different biometrics computed from the same hand image. Features extracted from each of the five fingers' surface areas were fused at the score level into a single mode.	The multimodal system produced RR, FRR and FAR of 96.80%, 2.90% and 0.31%, respectively.	Bad data acquisition is responsible for about 95% failed recognition.
Kounoudes et al. (2008)	Designed a multimodal biometric system that combined voice, face, finger and palm features using BOLYBIO datasets.	The multimodal system generated FRR and FAR of 0.86% and 1.23%, respectively.	The developed system was based on a small data set.
Zhang et al. (2008)	Combined three biometric traits of face, palm print and gait. Features were selected using the geometry preserving projections (GPP) algorithm. Two data arrays named YALE-HKPU-USF and FERET-HKPU-USF were built.	The recognition rate obtained using kernel GPP (KGPP) was 90.22% and 93.67 for the YALE-HKPU-USF and	The work was based on a limited data set.

Author(s) and year	Methodology	Results	Limitations
		FERET-HKPU-USF datasets.	
Patil and Jagtap (2020)	Developed a system that combined a finger knuckle and retina image based multimodal biometric authentication system using IITD and STARE database. Experiments were carried out at various threshold values of 0.40, 0.45, 0.50 and 0.55.	The threshold of 0.50 gave the highest GAR rate, 98.66%, and the lowest FAR of 0.33%.	Limited number of biometric traits were considered.
Aizi and Ouslim (2019)	Developed a multibiometric fusion of iris and fingerprints. Each modality was separately processed to generate a score vector. Features were fused at the score level. The score range was split into three zones of interest relevant to the proposed identification method.	The multimodal based on BCC achieved FRR, EFAR, FAR and RR of 3.89%, 1.11%, 1.50% and 95.00%, compared to those of BFL, which produced 5.00%, 0.56%, 2.50% and 94.44%.	The system was based on a non-real data set with a limited number of biometric samples.

3 Research methods

The biometric system developed in this study consists of the stages displayed in Figure 1.

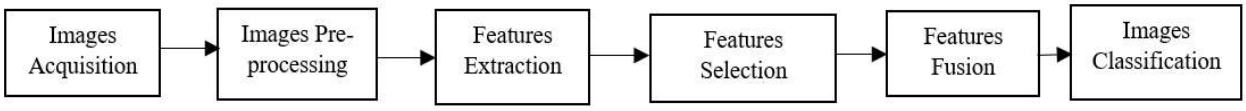


Figure1. *Workflow diagram of biometric system developed.*

Data acquisition: Five biometric traits were considered in this work. These include faces, fingerprints, irises, voices and signatures. The traits were collected from 200 black people of different age groups, and three samples of each trait were collected from each individual. This is equivalent to $3 * 5 * 200$, making a total number of 3000 biometric evidence items. A CMITech camera was used to capture faces and irises, an android phone voice recorder and a Topaz T camera were used to capture fingerprints, voices and signatures, respectively. The devices were located very closed to each other for easy access, and all data were captured in an uncontrolled environment. It is hoped to make the data available online for the benefit of researchers working in related fields. The biometric systems developed were implemented in MATLAB 2016b V.8.1.

Image pre-processing and segmentation: this was achieved by carrying out error elimination, pattern localization and detection of the interest aspects of the acquired biometric traits using Hough transform for faces, fingerprints and signatures. The following were done to segment the iris from eye images. Eye images went through image conversion to greyscale, image normalization using histogram equalization, and the iris part was segmented out of the eye using Hough transform. Furthermore, Daugman's rubber sheet model converted the circular iris to rectangular form (vector form). Voice signals went through pre-

processing stages such as analogue to digital conversion, silence detection, pre-emphasis and windowing. Figure 2 shows some of the image pre-processing stages.

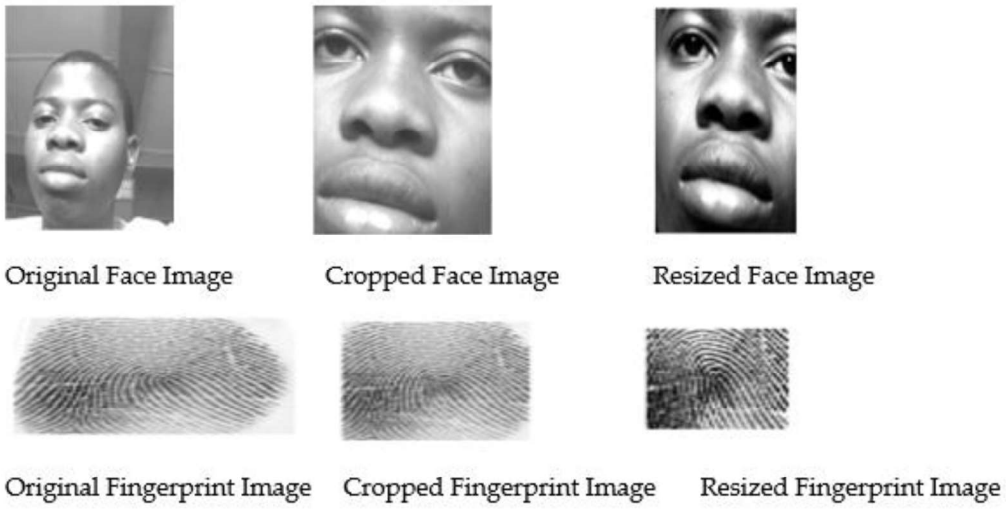


Figure 2. *Image pre-processing stages.*

Feature extraction: Features were extracted using Principal Component Analysis (PCA). PCA is one of the standard techniques used for feature extraction and data representation (Turk & Pentland, 1991). PCA does not only reduce the dimensions of the image but also preserves the distinctive features of the image data and delivers a compressed representation of an image. PCA has been profusely used in many areas of research ranging from neuroscience, telemedicine and security systems to computer graphics. PCA acceptance is due to its straightforwardness and also a non-parametric technique of mining pertinent information from complex data sets. With minor further effort, PCA delivers answers on how to minimize composite data sets by reducing the data dimension and still retaining the hidden features of the image. Its simplified dynamism often underlies situations without losing the essential features of the image.

Feature selection: This is the next stage after feature extraction. This phase encompasses a selection of the most relevant features of images before feature fusion. The Teaching-Learning Based Optimization (TLBO) algorithm was used to select the most salient features/detectors of all the biometric modalities considered in this work. The choice of the TLBO is based on the fact that it has the ability to provide a global solution to a large-scale nonlinear optimization problem (Rao et al., 2012). The TLBO consists of two phases: the teacher phase and the learner phase.

The **teacher phase** is the first phase of the algorithm at which the feature/detector/sample with the highest weight is seen as the teacher. The teacher is used to train the learners (rest of the sample spaces). At this stage, a teacher attempts to improve the knowledge/average/mean results of the rest of the sample space based on its capability. At any instance *i*, with *m* number of sample spaces (design variables) and *n* number of learners (population size (*s)* ranges from 1 to *n* and the average result ($M_{j,i}$) of the learners in a sample $j = 1, 2, \ldots,$ m. The overall best result $X_{total-kbest,i}$, obtained considering all samples in the whole population of learners, is seen as the result of the best learner k_{best}, which is always considered to be the teacher.

The teacher is considered the most learned (sample with the highest weight), who teaches learners to improve their results. Therefore, the algorithm recognized the teacher as the best learner. The difference between the current mean result of each sample and the equivalent result of the teacher for each sample space is as shown in Equation 1.

$$Difference_mean_{j,k,i} = r_i\left(X_{j,kbest,i} - T_F M_{j,i}\right) \quad (1)$$

Where $X_{j,kbest,i}$ = the result of the best learner (best sample space); T_F is the teaching factor, and r_i is the random number which ranges between 0 and 1; and $M_{j,i}$ is the average/ mean result of the learners in a sample.

The value of T_F is also chosen randomly to either be 1 or 2. This is done using equal probability, as shown in Equation 2.

$$T_F = round(1 + rand(0,1)\{1\}) \tag{2}$$

The algorithm is assumed to perform significantly better if the value of T_F is either 1 or 2.

Based on the $Difference_mean_{j,k,i}$, the current best solution is updated in the teacher phase according to Equation 3.

$$X'_{j,k,i} = X_{j,k,i} + Difference_Mean_{j,k,i} \tag{3}$$

Where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$.

$X'_{j,k,i}$ is accepted if it gives a better function value. All the accepted function values (sample spaces) at the end of the teacher phase are conserved and serve as the input to the learner phase. The learner phase is dependent on the teacher phase.

The learner phase is the second stage of the TLBO algorithm, at which the number of sample spaces is improved based on their interaction with one another. Considering a population size of n, the learning progression of this phase is described below.

Assuming two learners (features)' Y and Z are randomly selected, such that:

$$X'_{total-Y,i} \neq X'_{total-Z,i} \tag{4}$$

Where $X'_{total-Y,i}$ and $X'_{total-Z,i}$ are the two updated function values of $X_{total-Y,i}$ and $X_{total-Z,i}$ of the learners Y and Z, respectively.

Therefore,

$$X''_{j,Y,i} = X'_{j,Y,i} - r_i\left(X'_{j,Y,i} - X'_{j,Z.i}\right)$$

if $X'_{total-Z,i} < X'_{total-Y,i}$ ***OR*** $X''_{j,Y,i} = X'_{j,Y,i} - r_i\left(X'_{j,Z,i} - X'_{j,Y,i}\right)$

if $X'_{total-Y,i} < X'_{total-Z,i}$ (5)

With this feature selection process, all the extracted features from an image are equally considered and sampled, whereby the best are selected to represent the image during feature fusion. The feature selection analysed above was used to select features of all the modalities considered in this work.

Feature fusion: The weighted average method was used for feature fusion. Feature fusion involves a mixing of all features extracted from the five biometric traits. Since the modalities considered in this work are heterogeneous, feature normalization was done using the min-max normalization technique.

$$weighted_{Ave} = \frac{1}{m}\sum_i^n w_i.score_i \tag{6}$$

Where m is the value used to normalize the score (ranges from 0-1), n is the total number of modalities, w is the weight of every single modality, and $score_i$ is the matching score of every single modality.

Min-max method: This method is used to rescale the extracted feature sets or data. It can transform data sets into smaller sizes and bring data sets with different weights into a common range. This is done by transforming all feature sets with a minimum value to 0. Those with a maximum value are transformed to 1. Every other maximum and minimum value is transformed into decimals between 0 and 1. In this method, a linear transformation is performed on the original data. For instance, suppose Max_Y and Min_Y

are the maximum and minimum values of an attribute Y. Then, min-max normalization regulates the value V of Y to Y' in the range $[new_min_Y, new_max_Y]$ by computing:

$$V' = \frac{V - min_Y}{max_Y - min_Y}(new_max_Y - new_min_Y) + new_min_Y \quad (7)$$

Where v is the original weight of the data, $v'$is the normalized weight of the data, max_y is the maximum weight of a data item, $min_y$is the minimum weight of a data item, $new_max_Y = 1$ and $new_min_Y = 0$. The feature fusion is followed by image classification using the ONSA.

3.1 Formulation of Optimized Negative Selection Algorithm

The ONSA is an optimized version of the Standard/Traditional Negative Selection Algorithm (SNSA). The NSA is one of the nature-inspired algorithms that mimic the way the mammalian immune system differentiates between normal body cells (antibodies) and external body cells (antigens). The NSA has been used to solve many problems ranging from spam detection, anomalous detection and intruder detection systems among others (Chikh & Salim, 2017).

However, the random feature selection employed by the SNSA makes it prone to problems such as lack of continuous learning ability, generated features that do not entirely cover the non-self-space and lots of redundant coverage among features. Hence, this research optimizes the feature selection process of the NSA using the TLBO algorithm to solve the limitation of the SNSA mentioned above. The choice of the TLBO over other optimization algorithms is due to its inherent benefits of being able to yield optimized solutions within a brief period of the learning process. This is a result of the fact that the TLBO does not require the tuning of any algorithm-specific parameters besides the common ones.

Algorithm for training with TLBO

BEGIN

$G \leftarrow 0$

Initial_population (feature, feature_size)

Estimate (s)

Determine _fitness (s)

Repeat

{Teacher phase}

R = random (0 to 1)

$T_F = round(1 + r) * (1 \; or \; 2)$

$X_{mean} \leftarrow determine_mean_{vector}(D)$

$X_{teacher} \leftarrow Best_{feature}(D)$

Difference_vector = $(r.(X_{teacher} - T_F V_{mean}))$

$X_{new,i} = X_{old.i} + Difference_vector$

Calculate (X_{new})

{ Calculate_fitness (S)}

if $X_{new,i}$ is fitter than $X_{old,i}$ **then**

{Match_fitness (S)}

$X_{old.i} \leftarrow X_{new,i}$

end if {END OF TEACHER PHASE}

{Learner phase}

$j \leftarrow$ random (feature_size) Where $\{j \neq i\}$

if X_i is better than X_j **then**

$X_{new,i} = (X_{old,i} + r)(X_i - X_j)$ **else**

$X_{new,i} = (X_{old,i} + r)(X_j - X_i)$

end if

Calculate $X_{new,i}$

{Calculate_fitness()}

if $X_{new,i}$ is fitter than $X_{old,i}$ **then**

{Compare_fitness ()}

$X_{old,i} \leftarrow X_{new,i}$

end if {END OF LEARNER PHASE}

End

end {END OF LEARNER PHASE}

for $\boldsymbol{G \leftarrow G + 1}$

until $(G = New - gen\ \{Termination_condition\})$

Output Best_Result

end for

End

3.2 Formulation of ONSA using TLBO

If n_a is a counter that counts the number of self-tolerant Artificial Lymphocytes (ALCs) to be trained, as shown in Figure 3.

BEGIN

Formulate an empty set of self-tolerant ALCs as *C*;

With a training set of self-patterns (query pattern) denoted as D_T;

While $C \neq n_a$ **Do**

Create an ALC, x_i using TLBO;

Match = False;

For each self-pattern $Z_p \in D_T$ **Do**

If affinity between x_i and Z_p is greater than affinity threshold *r* **then**;

Matched = true;

Break;

end If

end For

If match = false

Then $x_i$is added to set C

end If

End

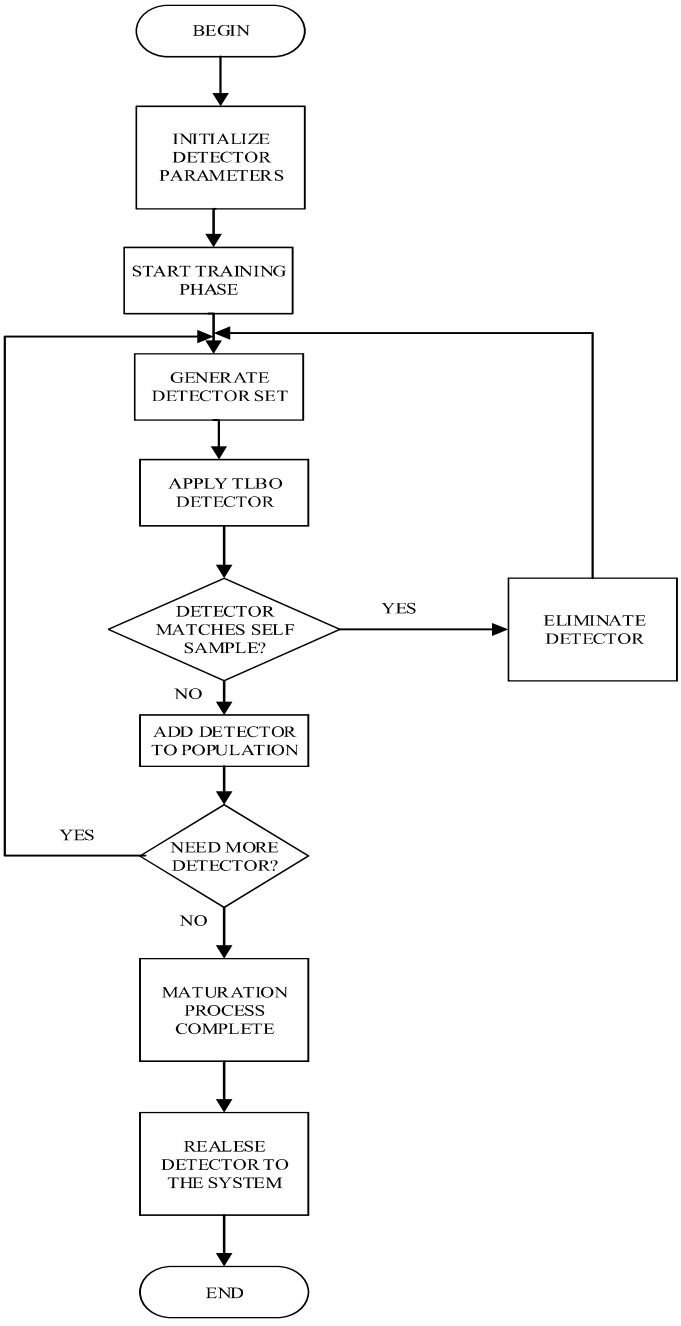


Figure 3. *Flow diagram of optimized algorithm (ONSA).*

The first time an individual is exposed to a biometric system is called enrolment. At this stage, biometric information is collected from the person and subjected to all the processing stages and then stored in the system database (identity creation). The created identity can then be used for identification or verification purposes in the future. Figure 4 presents the block diagram of the multimodal biometric system

developed, while the graphical user interface for the implementation of the multimodal system developed is displayed in Figure 5. It can be seen from the figures that traits were collected and processed in a parallel manner, so that all the traits have to be provided anytime there is a need to access the biometric system. This makes the system more robust and difficult for hacker attacks.

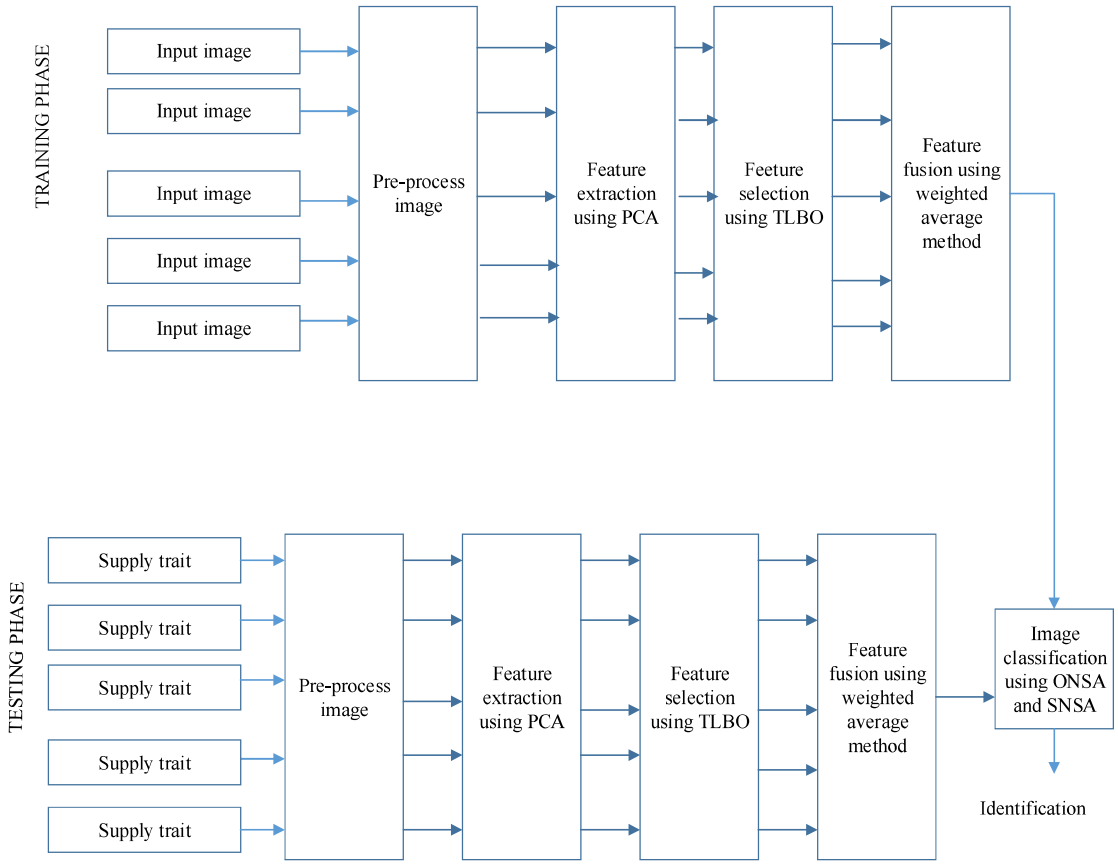


Figure 4. *Block diagram of multimodal biometric database system developed.*

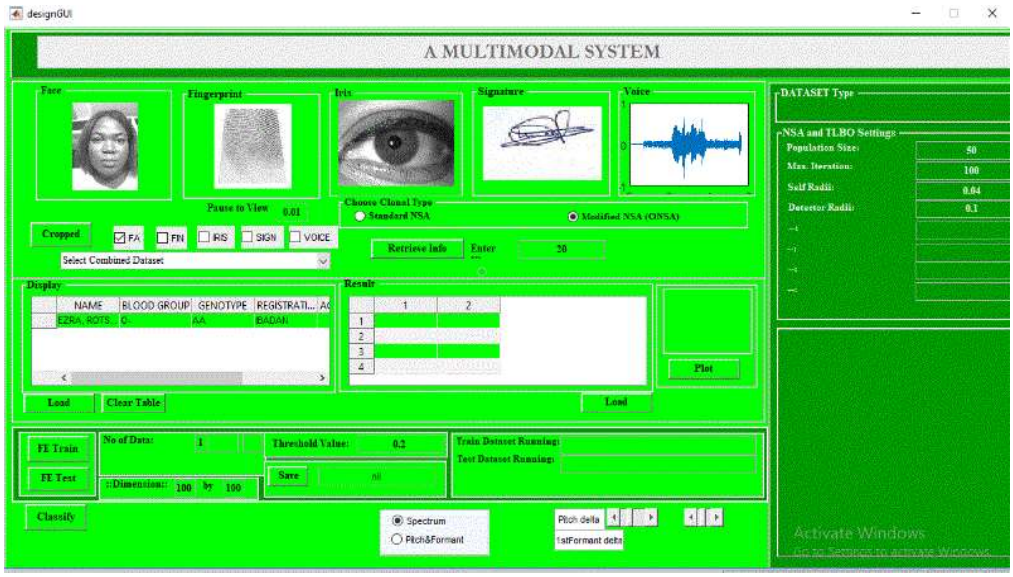


Figure 5. *Graphical user interface for multimodal system.*

4 Results and Discussion

The performance of the optimized algorithm (ONSA) was compared with that of the standard algorithm (SNSA) using the following performance evaluation metrics: true positive (TP), true negative (TN), false positive (FP), false negative (FN), false acceptance rate (FAR), false rejection rate (FRR), accuracy and processing/recognition time.

Table 2. *Comparison of TP, FN, FP and TN of ONSA and SNSA in multimodal biometric system developed.*

Metrics	ONSA	SNSA
TP (%)	146.00	143.00
FN (%)	4.00	7.00
FP (%)	1.00	4.00
TN (%)	149.00	146.00

TP and TN are used to determine the rate at which a system correctly accepts or correctly rejects a query data item, respectively. At the same time, FP and FN are the rates at which a system incorrectly accepts or rejects a query data item. It can be seen from Table 2 that the ONSA produced TP and TN values of 146% and 149%, respectively, while the SNSA produced 143% and 146% for TP and TN, respectively. Also, the ONSA generated a lower FN and FP rate of 4.00% and 1.00%, respectively, compared to the SNSA, which generated FN and FP values of 7.00% and 4.00%, respectively. It can be deduced from these results that the ONSA has higher recognition accuracy than the SNSA because the lower the false acceptance rate or false recognition rate generated by a system, the more accurate the system. This indicates that the global feature selection employed by the ONSA improves the recognition accuracy of the biometric recognition system. This is in line with Thakur and Maheshwari (2017). Figure 6 also buttresses the fact established by Table 2 by showing that the ONSA produced higher true recognition values and low false recognition values than the SNSA.

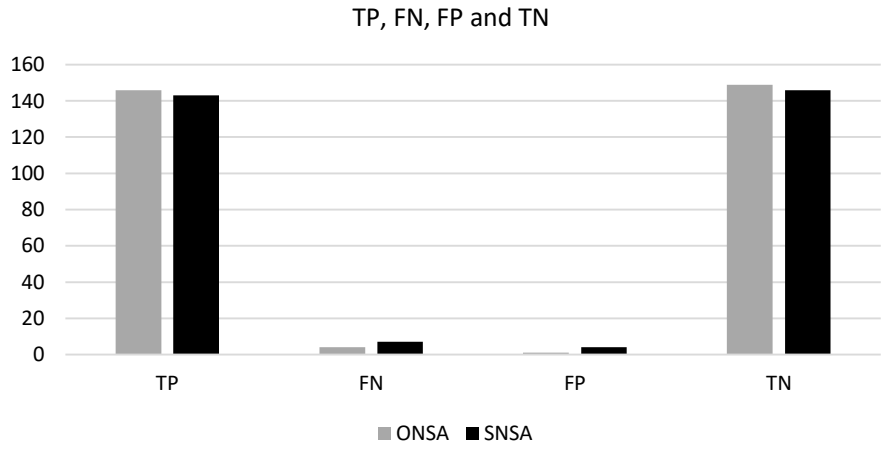


Figure 6. *Comparison of TP, FN, FP and TN of ONSA and SNSA in multimodal biometric system developed.*

Table 3. *Comparison of FAR, FRR, accuracy and recognition time of ONSA and SNSA in multimodal biometric system developed.*

Metrics	ONSA	SNSA
FAR (%)	0.67	2.67
FRR (%)	02.67	4.67
Accuracy (%)	98.33	96.33
Recognition Time (s)	792.08	612.06

Displayed in Table 3 is the comparison of the FAR, FRR, accuracy and recognition time of the ONSA and the SNSA. It can be seen from the table that the ONSA produced the lower false recognition rate by generating FAR, FRR and accuracy values of 0.67%, 02.67% and 98.33%, respectively. The lower the false recognition rate generated by a system, the more accurate the system. This is in accordance with Singh et al. (2014). In comparison, the SNSA produced FAR, FRR and accuracy values of 2.67%, 4.67% and 96.33%. This also implies that the ONSA outperformed the SNSA. Even though the recognition time of the ONSA is 792.08 seconds, which is higher than that of the SNSA, which is 612,06 seconds, this is a result of the global feature selection employed by the ONSA. According to Hira and Gillies (2015) global feature selection improves the biometric system accuracy. However, the high recognition accuracy produced by the ONSA compensates for the time loss in the ONSA. Figure 7 and Figure 8 also show that the ONSA has better performance accuracy than the SNSA by indicating that the ONSA has higher accuracy values than the SNSA.

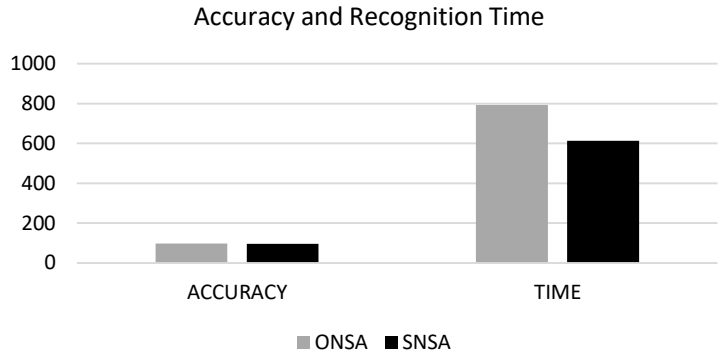


Figure 7. *Comparison of accuracy and recognition time of ONSA and SNSA in multimodal system developed.*

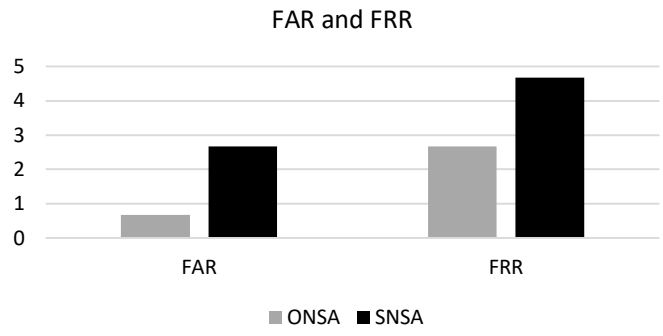


Figure 8. *Comparison of FAR and FRR rates of ONSA and SNSA in multimodal system developed.*

5 Conclusion

This study developed an ONSA to address the problems of incorrect representation of image features, improper training of classifier models for newly emerging data (over-fitting or under-fitting problem). The study also addressed the lack of an efficient mode of generating model parameters (scalability problem) associated with some existing classification algorithms. The random feature selection of the SNSA was replaced with the global feature selection using the TLBO selection in the optimized algorithm (ONSA). Therefore, the optimized algorithm developed can consider the whole self-space during detector/feature generation with associated high accuracy, low FAR and low FRR. The optimized algorithm developed was used as a classifier in a multimodal biometric system that fused face features, fingerprint, iris, signature and voice. This was done to validate its effectiveness. The performance of the optimized algorithm ONSA was compared with that of the SNSA, and it was discovered that the ONSA has a lower false recognition rate by producing lower FN, FP, FAR and FRR than the SNSA. The ONSA also generated higher true recognition by producing higher recognition accuracy than the SNSA.

Conclusively, the ONSA can be used as a classifier in any related identification system. The data acquired for this work, which will soon be available online, can be used by any researcher working on a human identification system.

The following are recommended future improvement on the algorithm developed. The recognition time (RT) of the optimized algorithm is high and this can be rectified by the following:

- The optimized algorithm (ONSA) can be hybridized with other types of artificial immune system algorithms such as a clonal selection algorithm to improve the biometric system recognition accuracy.
- Biometric images captured on the move (dynamic recognition) can also be used to evaluate the performance of the optimized algorithm.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: B.M.O.: Conceptualization, Methodology, Software, Data curation, Writing – Original draft preparation. O.L.A.: Visualization, Investigation. O.E.O.: Supervision. F.A.S.: Software, Validation. O.S.O.: Reviewing and Editing.

Institutional Review Board Statement: This study was approved on 27 January 2021 by the Post-Graduate Board, Ladoke Akintola University of Technology, Ogbomoso, Nigeria. Protocol number PGS/ROTT/122.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the research. Also, written informed consent has been obtained from all participants to publish this article.

Data Availability: The data that support the findings of this study are available from the corresponding author.

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