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Fuzzy Classification with Comprehensive Learning Gravitational Search Algorithm in Breast Tumor Detection

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***Abstract:** The research paper herewith presents an effectual diagnosis classification system using fuzzy classifier and a very efficient heuristics algorithm comprehensive learning gravitational search algorithm (CLGSA) which has a good ability to search and finding optimal solutions. The effectiveness of the proposed model is estimating on Wisconsin breast cancer data set available in the UCI Machine learning source in the University of California, Irvine. We testify the data over the parameters of classification of accurateness, sensitivity as well as specificity with a much better and more responsive 10-fold cross validation method; which is considered as a reliable diagnostics model in the medical field. Experiment results have clearly shown that the proposed approach will turn out to be a calculative and decisive medium for cancer detection in the field of medicine.*

***Index Terms:** Comprehensive learning Gravitational Search algorithm, Fuzzy classifier, Breast Cancer Diagnosis, Heuristic Optimization*

I. INTRODUCTION

Cancer is an uncontrolled mitotic activity of the cells in the bones, muscles, or anywhere in the organs. The majority of cancers are tumors, and which is the reason that tumors are invariably used for the cancers and vice versa. While tumors are not necessarily be life threatening, but cancers tend to become lethal for existence and sustenance of life. Breast cancer ranked amongst the second most dreadfully lethal and pervasive cancers in women [1]. According to the studies done in the US, it is believed that probability of a woman with breast cancer suffering a quietus is settled at 1 in 37, which is 2.7 percent. In the year 2017, there were approximately 252, 710 diagnoses of breast cancer, of which 40,610 women may die. DITI (Digital infrared thermal imaging), MRI (Magnetic Resonance Imaging), CT (Computed Tomography) Scanning, Mammography and Thermography have been a valuable resolution against the ultrasound imaging. Generally, breast cancer diagnosis is classified as two ways: benign and malignant. A benign tumor does not attack its nearby tissue or spread around the body. A malignant tumor may attack its nearby tissue or spread around the body. Most cancers are spotted as a protuberance on the breast during your own personal examination and even by means of diagnostic instrumentation like mammography [2]. This diagnostic instrumentation is the most widely used screening tool for detecting breast cancer before clinical symptoms begin to appear [3]. Many other techniques using image processing [4], [5], such as in the case of gene expression approach [6],[7], Support vector machine [8], Boolean rule for neural network [9],[10], k- nearest neighbour [11],[12], fuzzy logic [13], have been applied, but in these cases techniques was very weak in assessment of the results and practically infeasible due to increased computational time. Hence, the researcher worked upon the advanced hybrid evolutionary computational techniques, relevant in the medical field. Improved genetic algorithm that has been introduced with fuzzy classifier methodology [14] is applied for cancer diagnosis on Wisconsin breast cancer data set. In the same manner, the nature-inspired gravitational search algorithm (GSA) along with fuzzy classifier is applied for ameliorating the range of features [15] by dividing the whole swarm into parts. Although GSA is an effective technique but has long execution time due to lack of memory [22] and stuck in local optimums. Hence in this paper, we applied an updated version of gravitational search approach named Comprehensive Learning Gravitational Search Algorithm (CLGSA) [16], regardless of GSA; CLGSA carries memory and comprehensive search ability that makes this approach more efficient and popular. Along with fuzzy classifier increase the speed of algorithm. This experiment will be conducted on the Wisconsin Breast Cancer Database (WBCD), this typical database has been excessively and quickly available for study [17]. The paper is categorized into various sections for the ease of understanding. Section II describes the Comprehensive Learning Gravitational Search Algorithm (CLGSA) Section III gives a brief description fuzzy based rule classification, Section IV, describe the proposed method CLGSA approach using Fuzzy classifier, Section V, presents
computational results and analysis, Section VI discuss the results and section VII conclude the paper.

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II. COMPREHENSIVE LEARNING GRAVITATIONAL SEARCH ALGORITHM (CLGSA)

The idea of CLGSA [16] is based on a very famous heuristic algorithm GSA[18] presented by Rashedi et al. in the year of 2009, based on isolated groups of masses, and strictly adhering to Newton's gravitational laws of motion. CLGSA is a nature-inspired algorithm, but with better optimization to several problems, in comparison to several similar natural algorithms such as GSA PSO and many more. CLGSA considers the fact that the Newtonian algorithm needs only two significant parameters -swarm size and gravitational coefficient, and each of these parameters is used in specifying penetrating and probing capabilities of CLGSA like – population exploration, premature convergence, speed, capturing candidate solution, and many more. In recent times, CLGSA is being used in resolving critical optimization issues in various fields, besides medicine only [22].

A. Physical Elucidation of CLGSA on Newtonian Mechanics

Newton's gravitational laws form the basis of CLGSA. According to these laws, in nature, every particle will attract another particle by exerting the gravitational force [19]. This force has a direct proportion to output calculated as multiplication of particle masses and shows an indirect proportionality to the product of distances existing between the particles**.** Let us consider n -dimensional search where each particle has a mass within the system of masses ($m_i\, for\; i = 1,2..n$) w.r.t. the above described Newton's Law, force F_{ij} will be described as:

$$F_{ij} = G \times \frac{m_i \times m_j}{r_{ij}+\varepsilon} \times (x_j - x_i);\quad i,j = 1,2,\dots,n \tag{1}$$

Where G gravitational constant, can be calculated as

$$G = G^{t_0} \times e^{-\alpha\frac{itr}{\max itr}} \tag{2}$$

Where α is decreasing coefficient with time and G^{t_0} is an initial value of G, itr , $maxitr$ are current and maximum number of predefined iterations respectively. In equation (1), ε is a small constant, r_{ij} represents the Euclidean distance among particles i and, manipulated in the form of magnitude:

$$r_{ij} = \left\|x_i - x_j\right\|_2 \tag{3}$$

The total force exploits on masses by the following equation:

$$F = \sum_{j=1, j\neq i} rand_j F_{ij} \tag{4}$$

Where $rand_j$ are random numbers generated in the interval [0, 1]. Therefore, with the help of the second law of motion, in accordance with Newtonian Mechanics, the acceleration a_i as ith agent is deduced through the equation:

$$a_i = \frac{F_{ij}}{m_i} \tag{5}$$

In the CLGSA approach, the finest of the swarm agent will improvise itself by taking into account all the information from various associated components. In this respect, the velocity and location

$$v_i^{t+1} = rand_i \times v_i^t + a_i^t \tag{6}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{7}$$

More mass value characterizes a competent agent (which gives out a prominent solution for detecting cancer). In addition to this, due to the higher force of attraction, the heavier mass will produce an influence over the movement of other particles, which eventually results into a significant solution.

$$m_i = \frac{fit_i - worst}{best - worst} \tag{8}$$

Where fit_i represents the fitness value of ith agent, $best$ and $worst$ can be the best prominent solution, or possibly the worst element for detecting cancer tissues. The movement of masses/ agents played a very imperative role in detecting cancer. Therefore, without loss of generality,

$$\sum_{i=1}^{n} m_i = m \tag{9}$$

The fitness value of masses m is considered also as a fuzzy strength parameter which updates until gets the best fitness value. The aim of m is to judge the distances existing between the heavier masses, carried out on the basis of calculations with respect of associated masses, which are also contributing to the fitness or the value each associated member.

Algorithm 1. Pseudo-code of CLGSA.

Initialization

Generate random elements as $(x_{p1}x_{p2}\dots x_{pn})$ in search range size$[x_{minium}, x_{maxium}]$.

Evaluate the fitness value $(fit_1, fit_2, \dots, fit_n)$

$\boldsymbol{for}\; i = 1{:}n$

Calculate $G, best, worst\; and\; m_i\; by\; eq$ (2)&(8), $i = 1,2,\dots,n$

Calculate total force F_i by equation (1)

Calculate acceleration and velocity by equation (5), (6) and (7)

$\boldsymbol{for}\; i = 1{:}n$

Set learning probabilityP_c,

$if\; rand() < P_c$

Choose$[x_{p1}] = x(ceil(rand * n),);$

$\&[x_{p2}] = x(ceil(rand * n),);$

Find fitness value of these agents

$if(fit[x_{p1}] > fit[x_{p2}])$

$x_{pb} = [x_{pb};\, x_{p1}(i)];$

$else$

$x_{pb} = [x_{pb}, x_{p2}(i)];$

end

$else x_{pb}(i) = x_{best}(i);$

$end$of$\boldsymbol{for}$

Update $G, best, worst\; and\; m_i$

Calculate $a_i\; and\; v_i$

Go to step 2.

$end\; \boldsymbol{for}$

III. FUZZY RULE-BASEDCLASSIFICATION

The unique classification method is used for subjugating problems [20] while reducing the fuzziness in imaging. Significant methodologies are referred as well as projected for precise generation of fuzzy if-then rules for solving medical related problems [21]. The classifier derived from disorderly and unseen sampled data from the classes that already exist there. For simplifying, In order to simplify the understanding, we take the above-assumed n dimension data set $x_p = (x_{p1}, x_{p2} \dots x_{pn})$ with C classes, the consequential class C_i and uncertainty grade CU_i .

By if-then fuzzy rule [23] grade of certainty will be determined by two steps:

Step#1

A. Calculate

$$\beta_{class\ h}(i) = \sum_{x_p \epsilon class\ h} \mu_i(x_p)\, \mu_i(x_p) = \mu_{i1}(x_{p1}) \dots \mu_{in}(x_{pn}) \quad (10)$$

Where $\mu_i(x_p)$ represents fuzzy membership function

Step#2

B. Find $Class\ h$ that has the maximum value of $Class\ h(i)$:

$$\beta_{class\ h}(i) = \max_{1 \le k \le C}\{\beta_{class\ k}(i)\} \quad (11)$$

Hence

$$CU_i = \frac{\beta_{class\ h}(i)}{\sum_h \beta_{class\ h}(i)} \quad (12)$$

It is not the first time that the fuzzy if-then rule-based classification system brings out the functional results in the area of medical research, but with this system of classification, there is a very high probability of defining the pattern classification in all cases of digital imaging. The patterns formed within images are classified with the help of fuzzy if-then methodologies, give good results and clear-cut identification of cancer or tumor formations. This kind of identification will result in the betterment of solutions, and high image precision. Here, the implication also relates to the manners by means of which pattern space is being partitioned and the granular structure is in the images are observed.

The fuzzy if-then rules after analysis of the numerical data give primarily includes- division of pattern spaces within the subspaces, which seemingly appear fuzzy and resolution of fuzzy if-then rules for specified partitioned pattern spaces that appear in images. The presentation of this special kind of classification system is the result of the selection of fuzzy partitions that are drawn from the sampling or training patterns of the researches. However, there exists the anomaly in if-then rules, where the fuzzy pattern becomes massive and training patterns are not available for deducing the results.

It is quite significant to find that classification of patterns in all cases of events and other procedures are derived from the training samples as discussed in the data researched by the researchers. All the newly researched data is assigned to classes that have been pre-defined.

IV. THE PROPOSED DIAGNOSIS SYSTEM

This section is going to highlight a proposed Fuzzy based CLGSA (FCLGSA) diagnosis system. The approach has two stages: feature reduction and prominent or optimal parameter pair. The classification tasks are achieved using these stages. The first stage reduced the search space by eliminating irredundant or non-optimal elements and 2nd stage increases the efficiency of the solution and finds the global or best parameter. These trained feature solutions set applied further using 10-fold cross-validate system to get the best optimal parameters.

A. Fuzzy Classification Using Comprehensive learning Gravitational Search algorithm (FCLGSA)

This approach is based on fuzzy classification, where CLGSA - efficient algorithm is used for finding the global or best solution; CLGSA has the ability to solve multi-problem solution having more than one solution. Due to its comprehensive search, every element is examined and due to its impressive memory carrying properties, CLGSA is capable of storing, until getting the new better solution. Here, in the breast cancer diagnosis system, CLGSA help to find cancer in a search range by all available possible ways. It's also reduced the randomness of considering fuzzy set. The proposed algorithm first reduces the search space by eliminated the irredundant feature so that classification performance can be enhanced. In 2nd stage, every redundant feature shows remarkable improvement through own experience or by means of other member experience.

Procedure- Our prime consideration here is Wisconsin breast cancer datasets available in the UCI machine learning repository [17]. Represent this cancer data set as a matrix M whose columns represent the feature and rows are instances. Then the data set is normalized to the range [0, 1]. CLGSA first chooses redundant solutions set by the comprehensive approach and again cross-validate this set on k fold system, where k is given the value 10 here. The process is continued until the best solution pair (k,m) is reached, where k is set at 10 fold and m is considered as a fuzzy strength parameter.

Algorithm 2. Pseudo code of FCLGSA

Performance evaluation by using k-fold cross validation where k =10*/

$Begin$
$for\ i = 1{:}M$
$\quad for\ j = 1{:}k$
$\quad\quad fitness\ set\ = \ k - 1\ subsets$

Find grade of uncertainty and refine the element strength through membership function by$equation\ (10) and\ (12)$

Train the FCLGSA model on fitness set for finding optimal fuzzy strength parameter m, where k is set to 1,3,5,7respectively

Set assign accuracy to vector $v(j)$

end for

Compute mean value of vector v and stored in $M(i)$

$end\ for$

Get best m value where accuracy is highest in $M(i)$, stored as (k, m)

end

This section is going to highlight a proposed Fuzzy based CLGSA (FCLGSA) diagnosis system. The approach has two stages: feature reduction and prominent or optimal parameter pair. The classification tasks are achieved using these stages. The first stage reduced the search space by eliminating irredundant or non-optimal elements and 2nd stage increases the efficiency of the solution and finds the global or best parameter. These trained feature solutions set applied further using 10-fold cross-validate system to get the best optimal parameters. Fig.1.describes the procedure of proposed approach.

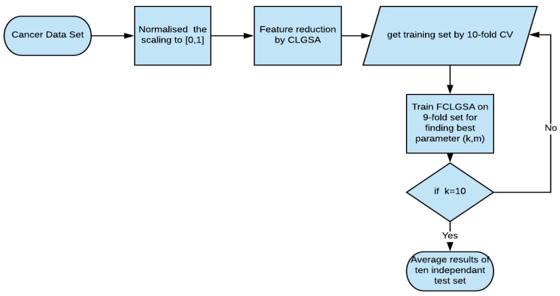

Fig. 1. Overall procedure of the proposed FCLGSA-based diagnosis system.

In the usual type of GSA, the scope of the swarm size has the constant value, but by regulating GSA through mathematical modelling. The fuzzy comprehensive learning GSA will prove a decisive tool in regulating the extent of a difficult process to deal with problems associated with medical imaging, particularly in the context of breast cancer.

V. NUMERICAL RESULTS AND COMPUTATIONAL ANALYSIS

A. Experimental Set up

In this study, the performance is carried out on the Wisconsin breast cancer data set available in the UCI Machine learning repository. This data set consists of 699 ten dimensional vectors, in which figure 458 is for benign and 241 stands for malignant cancer. To extend the fuzzy diagnostic system, the data set is partition into - training and testing set. Out of the 683 data, 228 data is considered for testing and the rest 455 data is intended for training. The testing data evaluate the performance of classifier and training set to find the optimal fitness. The attribute features are in Table 2. In this table, we consider nine features for simulation because the remaining sample codes are not relevant here.

The proposed Fuzzy CLGSA method is applied in MATLAB and implemented in a PC with micro processing speed 2.40 GHz and 256 MB of RAM. We compare the results of FCLGSA $(k = 1,3,5,7)$ with Thermograph Fuzzy Classification (TFC) [24] and Improved Genetic Fuzzy system (IGA) [14]. Population size is considered as 30 and maximum iterations are taken 1000. The features of these algorithmic values fall in line with the settings provided initially, and furthermore, these are also consistent with the researches. The parametric iterations of the projected model are provided in Table 1.

Table 1. Parameter Setting of Proposed Approach

n	Max iter.	P_c	α	G_0
30	1000	0.9	20	100

B. Measure of Performance Evaluation-Classification Accuracy (CA)

Sensitivity and Selectivity were used to evaluate proposed model. Classification accuracy here refers to the appropriately classified patients by their percent value; sensitivity is where the probability of identified as malignant is indeed malignant, and specificity refers to the probability of identifying the benign cancers, which are indeed benign in nature. We can use below formulas followed by Uncertainty Matrix in Table 3.

$$CA = \frac{T^+ + T^-}{T^+ + F^+ + F^- + T^-} \times 100\%$$

$$Sensitivity = \frac{T^+}{T^+ + F^-} \times 100\%$$

$$Specificity = \frac{T^-}{F^+ + T^-} \times 100\%$$

T^+ = Those cases where cancer is classified as cancer. T^- =Those cases where healthy person is considered as healthy person, F^- = those cases where cancer class is considered as healthy, F^+= those cases where healthy class is classified as cancer class.

Table 2. Attribute Information

Attribute Name	Range
Sample code number	ID code
Marginal Adhesion	1-10
Uniformity of Cell Shape	1-10
Uniformity of Cell Size	1-10
Single Epithelial Cell Size	1-10
Bland Chromatin	1-10
Bare Nuclei	1-10
Normal Nucleoli	1-10
Clump Thickness	1-10
Mitoses	1-10
Output Class	2 for benign, 4 for malignant

Table 3. Uncertainty Matrix

	Assumed Positive	Assumed Negative
Actual positive	True Positive (T^+)	True Negative (T^-)
Actual Negative	False Positive $((F^+)$	False Negative (F^-)

VI. OUTCOME OF THE RESEARCH

A. Results and Discussion

In order to verify the effectiveness of the FCLGSA model, it has been compared with other advanced classifiers. Fig. 2(a-d) shows the association between the classification accuracy and fuzzy strength m. Here, m in the range of 1 to 2 with step size is taken 0.01 using different values of k. In Fig2(a-d), it can observe that classification accuracy (CA) mostly fluctuates in 91% to 99% with different values of parameters (m, k). It reveals that m shows up prominent influence on the action of the proposed model. Here, the ideal classification accuracy is achieved with following (k, m) parameter pairs$(1,1.12), (3, 1.06), (5, 1.02)$and $(7, 1.28)$.

These optimal pairs are used in subsequent experiments, and for convenience, named as FCLGSA1, FCLGSA2, FCLGSA3, and FCLGSA4 for $k = 1,3,5,7$ respectively.

The detailed results in terms of Classification accuracy (CA), Sensitivity and Specificity are summarized in Table 4. The results are in the form of Minimal Accuracy (Min), Maximal accuracy (Max), Average classification accuracy (Mean) and Standard deviation (SD).

Table 4 shows that FCLGSA classifiers with different optimal pairs (k, m) are very close to one another. Among them, FCLGSA1 obtained maximum classification accuracy percentage (96.12) and sensitivity (96.60), while FCLGSA2 achieved the maximum specificity percentage that is, (95.82).

In table 5, proposed models are compared with other advanced models like - Thermography Fuzzy Classification (TFC) and Improved Genetic Fuzzy system (IGFS). The results in table 5, justify that FCLGSA classifiers are much superior in comparison to TFC and IGFS.

This can also be verified in Fig. 3(i-iii), where the comprehensive results of six classifiers FCLGSA1, FCLGSA2, FCLGSA3, FCLGSA4, TFC, and IGFS are presented. Fig. 3(i-iii) has shown the convergence of all six classifiers. FCLGSA classifier has less randomness and reached the highest value. It becomes quite stable after fluctuation. Each peak in the graph shows the good value of classifier. It can be easily seen that the FCLGSA approach presents better and stable convergence than others.

Table 4. Performance Results of FCLGSA with Different Optimal Parameter Pairs

FCLGSA	Performance metric	Min.	Max.	Mean	SD
FCLGSA1 k=1, m= 1.17	CA (%) Sensitivity (%) Specificity (%)	95.42 95.98 94.00	96.90 97.50 96.55	96.12 96.60 95.22	0.59 0.49 1.09
FCLGSA2 k=3, m= 1.04	CA (%) Sensitivity (%) Specificity (%)	95.10 95.56 94.00	97.10 96.50 97.75	96.05 96.01 95.82	0.87 0.54 1.99
FCLGSA3 k=5, m= 1.06	CA (%) Sensitivity (%) Specificity (%)	92.60 94.20 90.80	95.14 97.76 98.45	93.84 95.29 94.58	0.98 0.86 2.78
FCLGSA4 k=7, m= 1.02	CA (%) Sensitivity (%) Specificity (%)	94.28 94.10 92.60	96.45 96.78 98.40	95.29 95.42 95.48	0.72 0.51 2.01

B. Graphical Presentations depicting the Relationship Patterns

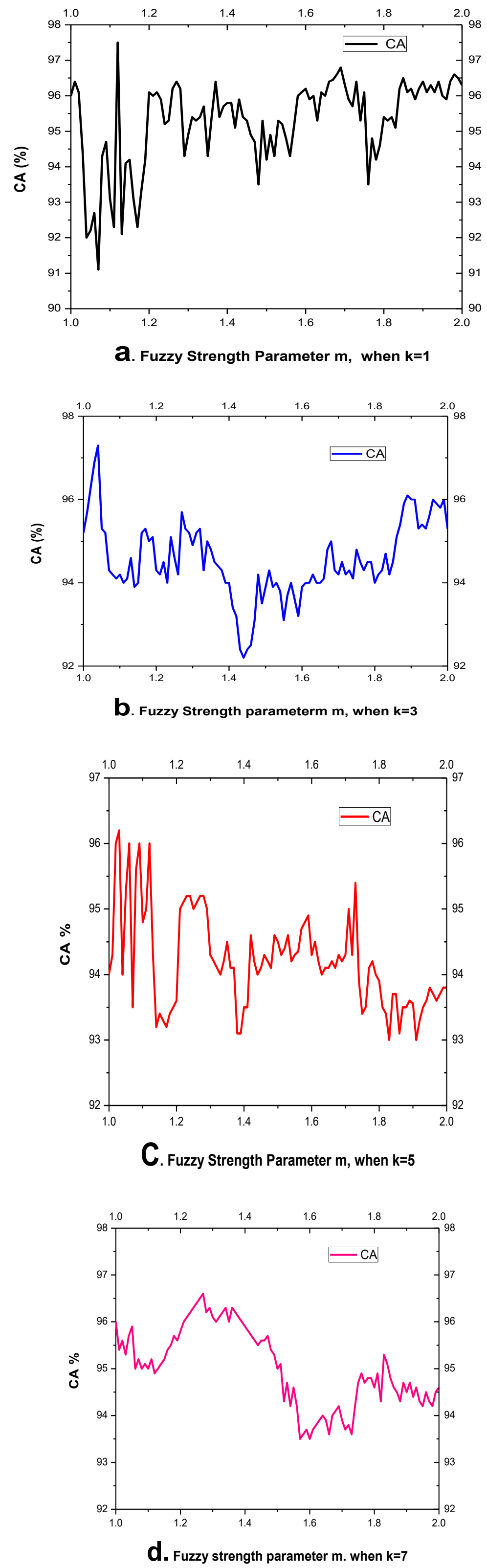

Fig. 2(a-d)the relationship between CA and fuzzy strength parameter m, with different value of k.

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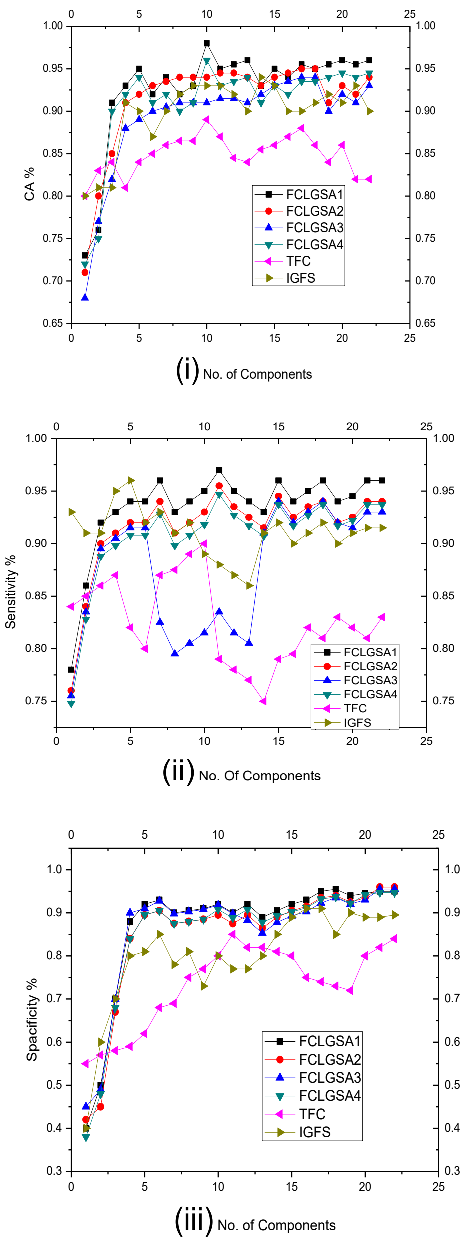

Fig. 3(i-iii).The Convergence graphs of CA, Selectivity and Specificity

Table 5. Comparative Results of FCLGSA Model with Other Models

Classifiers	CA (%)	Sensitivity (%)	Specificity (%)
FCLGSA1	96.12	96.60	95.22
FCLGSA2	96.05	96.01	95.82
FCLGSA3	93.84	95.29	94.58
FCLGSA4	95.29	95.42	95.48
TFC	80.12	84.56	85.10
IGFS	90.75	91.34	92.10

VII. CONCLUSION

This study introduces a new approach to cancer diagnosis. The main advantage of this model is applying a fuzzy classifier to a very novel algorithm CLGSA and cross-validate with 10-fold CV systems. Experiment results have shown that the proposed model performed well in distinguishing the cancer patients from the healthy ones. The performance of the FCLGSA model is evaluated by Classification accuracy, Sensitivity, and Specificity; hence, the conclusion is that the established diagnosis prototype can serve as an alternative tool for medical decisions, thus making it possible for an effective cancer diagnosis of the breasts.

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