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Design of Interval Type-3 Fuzzy Inference Systems for Medical Classification Using a Salp Swarm Algorithm

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Abstract. Detecting diseases in early stages allows patients to have a higher probability of success in their treatments, in addition to reducing treatment costs, which usually increase in advanced stages of various diseases. This is why intelligent techniques have recently become increasingly valuable for physicians, as they are capable of detecting patterns that a physician might not see or miss. This work proposes the optimization of Interval Type-3 fuzzy systems for disease classification. The structure of these classifiers is optimized using the Salp Swarm Algorithm, which searches the parameters of the membership functions of each input and their corresponding fuzzy rules. These optimized classifiers are designed using three databases: Immunotherapy, Cryotherapy, and Haberman's Survival, and where the average accuracy achieved is 84.72, 89.17, and 76.64, respectively. The results accomplished are compared with Type-1 and Interval Type-2 fuzzy systems designed by the same optimization algorithm, and with fuzzy systems designed using a different optimization technique.

Keywords. Salp swarm algorithm, medical classification, interval type-3, interval type-2, Sugeno model, fuzzy logic.

1 Introduction

Artificial intelligence has become an excellent ally for various areas of everyday life, such as virtual assistants, recommendation systems related to entertainment or commerce, smart cars, household appliances, and healthcare [17, 23, 30]. Currently, various applications have been implemented in the medical field, highlighting the importance of their implementation in areas such as diagnosis, monitoring, treatment, and rehabilitation [3, 29, 40]. Analysis of the application of artificial intelligence in medical devices, examining various techniques associated with deep learning and machine learning, concludes that artificial intelligence, alongside other technologies, is crucial for enabling more personalized medical care [6, 19, 36, 38].

Fuzzy logic (FL) is relevant in medicine because it enables the management of imprecision and uncertainty inherent in a field such as medicine.

This ability is applied in image analysis [5, 13], in systems that support diagnosis [10, 16, 41], and in the automatic control of medical equipment [4, 11], allowing for more personalized and precise decisions that support medical personnel [2, 20, 37]. In [15], the authors developed a method to improve the quality of stego medical images that integrates pixel differencing and FL. By grouping the image pixels into blocks, this method enables the separation of pixels in a methodical manner.

The difference between each pixel and the central pixel is calculated after the pixels are grouped. Applying FL successfully improves the quality of stego medical images, guaranteeing a higher quality. The results confirm the effectiveness of the FL application in the solution of medical problems. In [25], the authors collected data from thousands of patients, including non-neurological and neurological symptoms of COVID-19, which allowed them to identify moderate and mild cases. These attributes were utilized to design a fuzzy inference system to evaluate the diagnosis of COVID-19 using neurological symptoms as attributes.

The conduct of fuzzy systems depends on their configuration. Key parameters include those of the membership functions (MFs) and the fuzzy rules [12, 45]. It is for this reason that many works seek to find optimal parameters, mainly using optimization methods that allow improving the conduct of fuzzy systems (FS) compared to when they are used or developed by trial and error [7, 9]. Fuzzy systems have also been applied to support other techniques, creating new hybrid methods that allow improving the performance that each of the techniques would have individually [27, 32, 39]. Among the main optimization methods used in merger with FL, we can find genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and also the salp swarm algorithm (SSA) [18, 26, 28].

In [33], a GA is presented for the optimization of an Interval Type-3 fuzzy system (IT3FS) for its application in support of medical diagnosis. The GA was responsible for designing the FS, focusing on the parameters of the input variables, as well as the fuzzy rules and the values of the output constants, since Sugeno models were applied.

Comparisons were made using two types of MFs in the fuzzy inputs, where the results showed that the generalized bell (Gbell) MFs allowed obtaining better results in classification accuracy.

In this work, the optimization of IT3FS using a salp swarm algorithm is presented and applied to medical classification to create an effective tool to support medical diagnosis. The results accomplished with the method are contrasted with Type-1 fuzzy systems (T1FS) and Interval Type-2 fuzzy systems (IT2FS), in order to analyze whether the application of IT3FS is necessary or whether the application of another type of FL is sufficient. The results are also compared with the results obtained from the design of IT3FS optimized by a GA, presented in a previous work. The analysis presented in this work proves the effectiveness of IT3FS applied to medical diagnostic problems, mainly when evaluated with information not provided for their design.

This work is distributed as follows: Section 2 presents the concepts related to the implemented research approaches. The method, the description of the implementation of the different techniques used, and the description of the data used for the evaluation of the method are showed in Section 3. The results of the experiments, including a summary of the findings and statistical analysis are showed in Section 4. Section 5 concludes the analysis carried out in this work and outlines future work.

2 Basic Concepts

This section describes the essential concepts and approaches that underpin the work performed.

2.1 Fuzzy Logic

FL is an extension of classical logic introduced by L. Zadeh in 1965 [42, 44], created to address uncertainty and inexactness. It is suitable for solving complex situations and problems that cannot be easily defined using Boolean logic. This logic uses continuous values between [0,1] to establish a degree of belonging. It makes it easier to more accurately represent vague or ambiguous concepts that exist in real life. In 1975, L. Zadeh [43] proposed the idea of the Type-2 fuzzy set as an extension of Type-1 fuzzy sets. The Type-2 fuzzy set is distinguished by having a fuzzy MF, that is, the membership level of each of its elements is another fuzzy set in an interval [0,1], different from a Type-1 fuzzy set, in which membership is measured with an exact number in the same interval. The uncertainty region is defined by the footprint of uncertainty (FOU).

Type-3 fuzzy sets emerge to handle higher levels of uncertainty [22], where $A^{(3)}$ indicate a Type-3 fuzzy set, which represent a trivariate function, known as membership function of $A^{(3)}$, in the cartesian product defined in Equation 1:

$$\mu_{A^{(3)}} : X \times [0,1] \times [0,1] \rightarrow [0,1], \tag{1}$$

where X is the universe for the primary variable of $A^{(3)}$, x. The MF of $\mu_{A^{(3)}}$ is indicated by $\mu_{A^{(3)}}(x, u, v)$, and is a Type-3 MF of the Type-3 fuzzy set defined in Equation 2 [35]:

$$A^{(3)} = \{(x, u(x), v(x,u), \mu_{A^{(3)}}(x,u,v)) \mid x \in X,\, u \in U \subseteq [0,1], v \in V \subseteq [0,1]\}. \quad (2)$$

Where tertiary variable v has as universe V, and for the secondary variable u is U. The $FOU(\mathbb{A})$ for an Interval Type-3 Gbell MF depends of the lower membership function (LMF) and the upper membership function (UMF) to define $DOU = [\underline{\mu}(x), \overline{\mu}(x)]$. LowerLag ($\ell$), and LowerScale ($\lambda$) allows to define the LMF. The vertical cuts $\mathbb{A}_{(x)}(u)$, formed by Interval Type-2 fuzzy set with Interval Type-2 Gaussian MF are that distinguishes the $FOU(\mathbb{A})$. The $\mu_{\mathbb{A}_{(x)}}(u)$ is defined by UMF with parameters $[\sigma_u, m(x)]$, and LMF [8, 24].

2.1.1 Salp Swarm Algorithm

In 2017, the SSA was introduced [21], based on the behavior of Salps, which are marine animals that form chains to efficiently find food, where a salp plays the role of leader with various follower salps.

This algorithm models the navigation and foraging behavior of salps in the ocean. The followers stand behind the leader, forming a chain-like structure and adjusting to his movements. The algorithm begins by placing the salps in random positions to approach the global optimum. Determining the fitness of each solution (salp) is necessary to identify the one with the best fitness and establish which salp the others should follow. The coefficient c_1 is determined using Equation 3:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2}. \quad (3)$$

Where the current iteration is denoted by l, and L denotes the maximum number of iterations. This algorithm also uses as parameters c_2 and c_3 which are random numbers in [0,1]. The position update of the leading salp is determined using Equation 4:

$$x_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases}. \quad (4)$$

Where x_j^1 is the current position of the salp leader in the dimension j, F_j represents the position food, ub_j and lb_j denote the upper and lower bound, respectively. While the remaining salps update their position using Equation 5:

$$x_j^1 = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right). \quad (5)$$

When a salp leaves the delimited search space, it is returned to the established edges. The aforementioned updates are carried out iteratively until a stopping criterion is met [1, 31].

3 Proposed Method

The combination of IT3FS and an SSA is proposed to perform classification in specific areas related to medical classification. The SSA aims to establish the optimal design of the IT3FS, where the inputs of the fuzzy systems represent the attributes that characterize a specific illness or disease, and the output enables a diagnosis.

The proposed method can be applied to various classification problems because it allows for the design of 1 to n attributes. The proposed design of the IT3Fs developed by the SSA is illustrated in Figure 1. In this work, we test the effectiveness of the IT3FS designed for medical classification by implementing the SSA to optimize T1FS and IT2FS. This comparison allows us to compare results and determine whether the implementation of IT3FS is required.

3.1 Salp Swarm Algorithm for FS Design

The optimal design developed by the SSA consists of the parameters of 3 MFs in each input, the constant values (output), and the fuzzy rules of Sugeno Models. The values that allow for determining the search space for the input variables depend on the attributes established for each classification problem. The search space for the remaining parameters can remain fixed regardless of the classification problem established to prove the method in this work. These parameters, $LowerScale$ and $LowerLag$ (ranging from 0.1 to 0.9), enable the establishment of uncertainty, the setting of constant values (from 0 to 1) for the output, and the deactivation or activation of fuzzy if-then rules. An example of the inputs that will be optimized is represented in

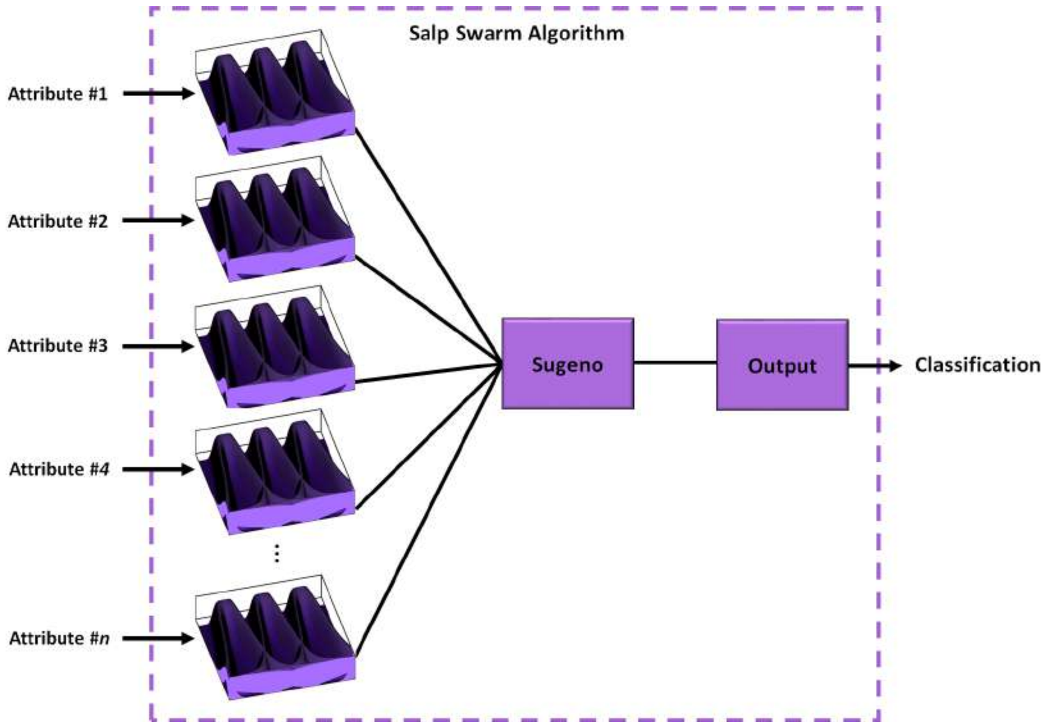

Fig. 1. Proposed design of IT3FS using an SSA

Figure 2, where an example of fuzzy variables of T1FS, IT2FS, and IT3FS can be observed.

For the evaluation of the fuzzy classifiers, Equation 6 and 7 are used:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100, \quad (6)$$

$$f = 1 - \frac{TP + TN}{TP + FP + TN + FN}, \quad (7)$$

where True Negative is TN, False Positive is FP, False Negative is FN, and True Positive is TP. Equation 7 is applied to establish the objective function implemented by the SSA to minimize classification error.

Table 1. Dataset's specification

Dataset	Atributes	Instances		
		Total	Design	Testing
Habermans Survival	3	306	184	122
Cryotherapy	6	90	54	36
Immunotherapy	7	90	54	36

3.2 Dataset Description

The SSA is used to design fuzzy classifiers, and three databases are implemented to analyze their effectiveness. The instances of each dataset are split into two sets: design set and testing set. In the execution of the SSA, the design set is utilized to minimize the error, and the testing set allows for assessing the real performance of the classifiers. Table 1 presents the distribution for each of the aforementioned sets, where 60% is allocated for design and the remaining 40% for testing the classifiers.

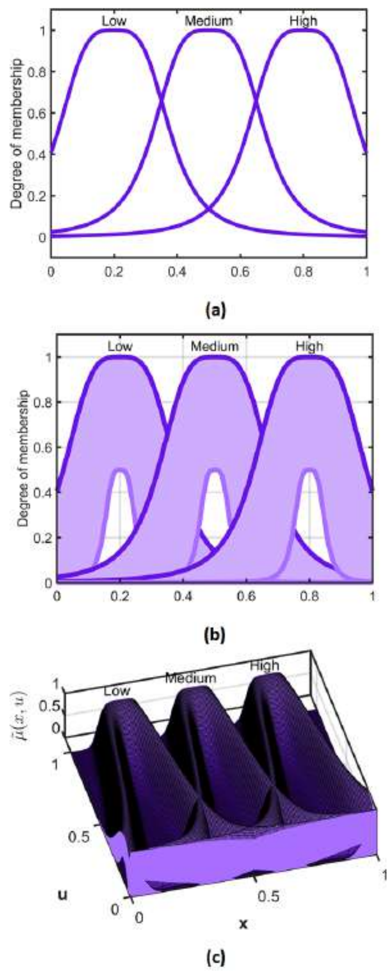

Fig. 2. Example of a) a Type-1, b) an Interval Type-2, and c) an Interval Type-3 Input

4 Experimental Results

The results of 30 experiments for each type of FL applied to the previously described databases are presented in this section. The results obtained with the design and the testing set, where the real performance of the classifier is evaluated, are shown. The SSA aims to achieve the optimal design of FS by searching for the parameters of the 3 GBell MFs for each input (depending on the database), the fuzzy rules, and the constant outputs of the FS. At the end of this section, a comparison with a previous work is shown.

Table 2. Results of Haberman's Survival dataset

FS	Phase	
	Design	Testing
T1FS	76.12	74.13
IT2FS	76.00	74.84
IT3FS	77.14	76.64

Table 3. Results of Cryotherapy dataset

FS	Phase	
	Design	Testing
T1FS	78.33	74.81
IT2FS	78.58	75.37
IT3FS	84.88	89.16

4.1 Haberman's Survival Results

The averages obtained with each type of FL are showed in Table 2, which shows the averages for each phase. These results demonstrate that for both phases, when the SSA designed IT3FS, the average accuracy increased.

The best IT3FS achieved 79.89% with the design set, whereas the best result with the testing set was 78.69%. Figure 3 shows the inputs of the IT3FS that obtained the best results with the design set for Haberman's Survival dataset. This fuzzy system has 14 of the 27 possible fuzzy rules.

4.2 Cryotherapy Results

In Table 3, the averages obtained with each type of FL are shown, showing the averages for each phase. It can be observed that the classification percentage also increases when using IT3FS.

The best results for the Cryotherapy dataset were achieved by T1FS and IT3FS, with 92.59% accuracy in the design phase. In contrast, IT3FS achieved the highest accuracy of 94.44% in the testing phase. In Figure 4, the best T1FS is shown; the configuration of this FS consists of 22 fuzzy rules. Meanwhile, the best IT3FS shown in Figure 5 has 30 fuzzy rules.

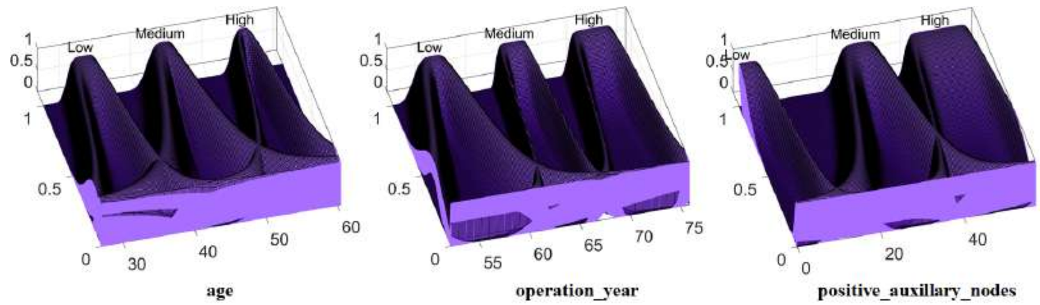

Fig. 3. Best IT3FS for the Haberman's Survival Dataset

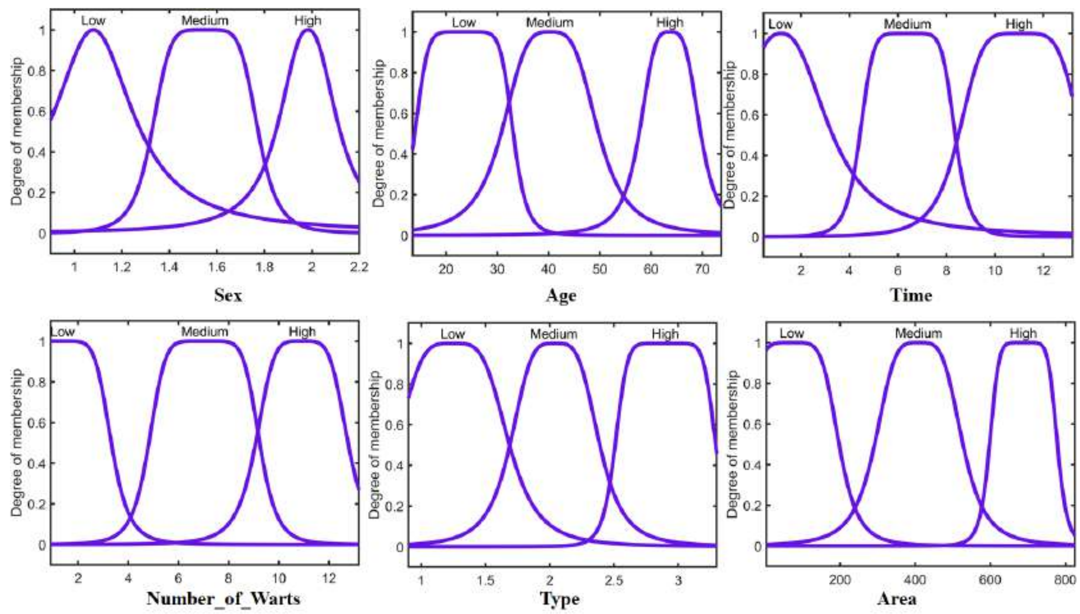

Fig. 4. Best T1FS for the Cryotherapy Dataset

4.3 Immunotherapy Results

The averages obtained with each type of FL are shown in Table 4, showing the averages for each phase when each type of FL is implemented, where it can be observed how the classification percentage is better using T1FS than IT2FS, but the best average is achieved with the IT3FS with the design set, however with the testing set, the accuracy increases according to the type of FL implemented.

The best results for the Immunotherapy dataset were achieved by IT3FS, with 90.74% accuracy with the design set and 91.66% with the testing set. In Figure 6, the best IT3FS is shown; the configuration of this FS consists of 138 fuzzy rules.

Table 4. Results of Immunotherapy dataset

FS	Phase	
	Design	Testing
T1FS	82.22	77.50
IT2FS	80.16	79.35
IT3FS	85.37	84.72

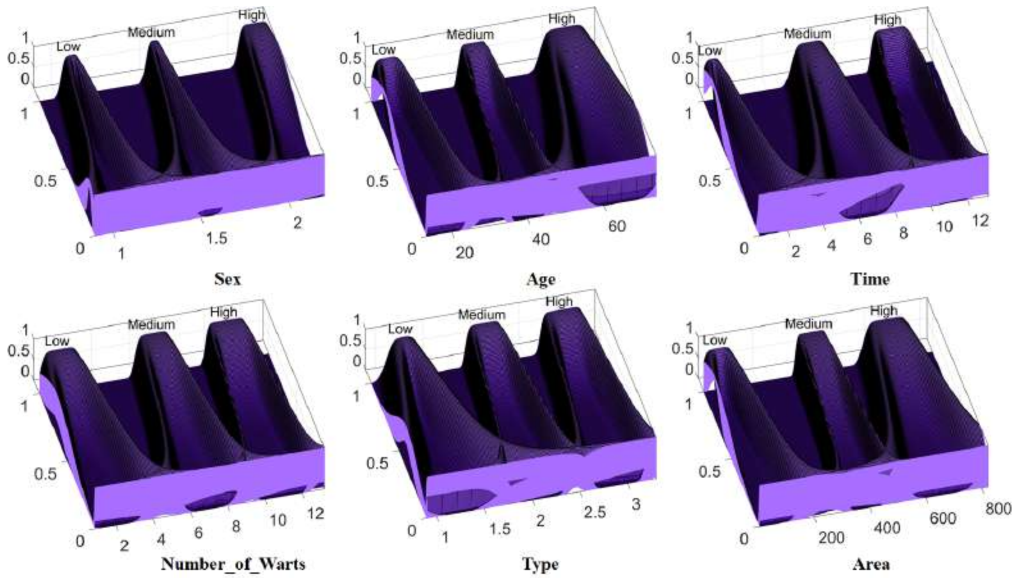

Fig. 5. Best IT3FS for the Cryotherapy Dataset

4.3.1 Summary of Results

The averages of convergence for each type of FL and the comparison with a previous work [33] where IT3FS were designed using a GA are shown in Figure 7, where it can be observed that for the Haberman´s Survival dataset when the GA designs the IT3FS the convergence has a better performance in the last five generations although the design of the IT3FS performed by the SSA has a better behavior than the other experiments in from generation 10 to 25. For the Cryotherapy dataset, the behavior is very similar. In the last generations, the GA has a better performance, but from generation 10 to 20, the SSA has a better convergence. Finally, for the Immunotherapy dataset, the IT3FS designed by the SSA clearly outperforms other types of FL and the IT3FS design developed using the GA.

As previously shown, the design determined by the SSA of the IT3FS provides a better percentage of accuracy. Table 5 presents the results obtained with the SSA-designed approach and those from a previous study, where IT3FS were also designed using a GA. Observation reveals that the GA (design phase) yields the best average for the first two databases. However, when evaluating the real performance of the designed IT3FS, the IT3FS designed by SSA demonstrates superior precision across all databases.

Table 5. Comparison results SSA vs GA designing IT3FS

Dataset	Optimization algorithm	Phase Design	Phase Testing
Haberman's Survival	SSA	77.14	76.64
	GA	77.35	76.50
Cryotherapy	SSA	84.88	89.17
	GA	86.67	88.15
Immunotherapy	SSA	85.37	84.72
	GA	84.07	83.61

4.3.2 Statistical Comparison

The archived results from the testing phase, conducted by the SSA and GA when designing IT3FS, are statistically compared in this section.

A significance of 95% is applied in the statistical Z-tests with 1.645 as the critical value. The null hypothesis (H0) is determined to indicate that there is no difference between the application of each of the optimization algorithms compared. In

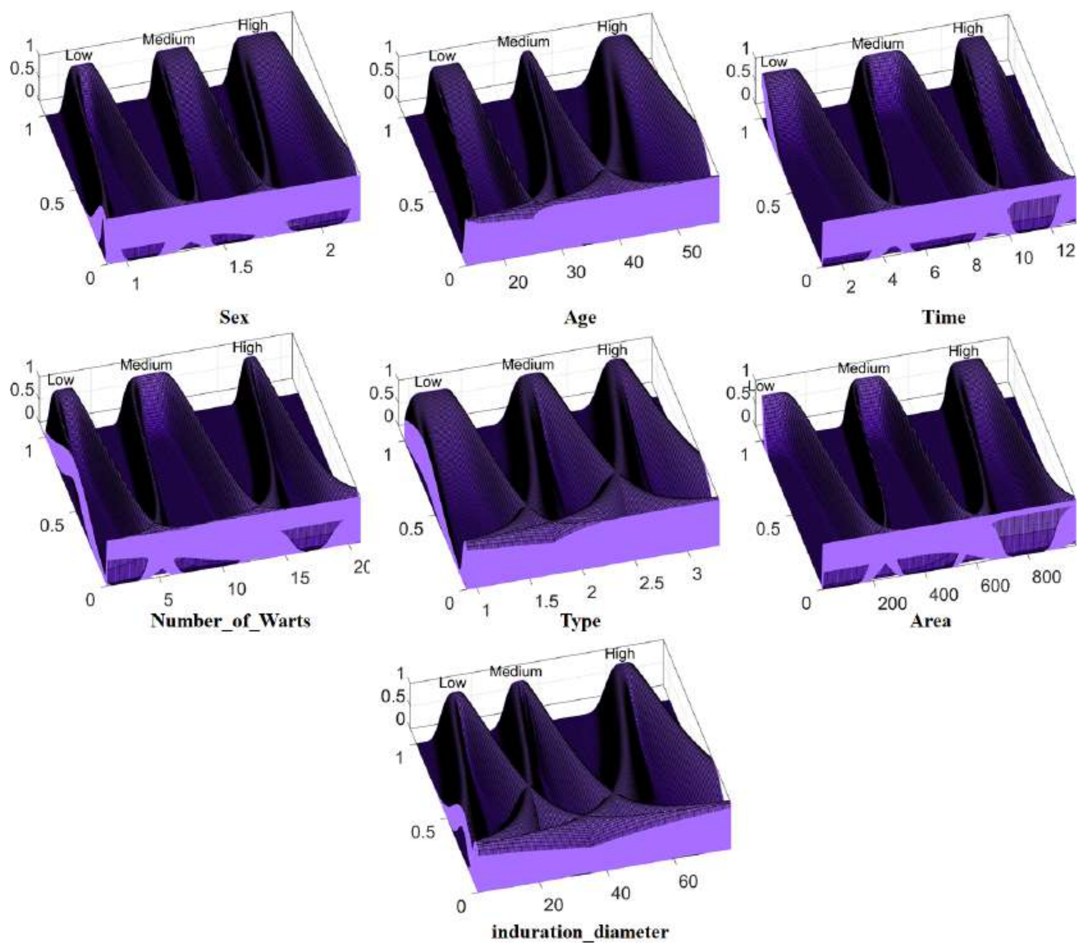

Fig. 6. Best IT3FS for the Immunotherapy Dataset

contrast, the alternative hypothesis (H1) means that there is a significant difference between the two optimization methods when used to design IT3FS. In Table 6, the values obtained for the Z-test are presented, demonstrating that the results achieved by the proposed SSA for the IT3FS design show a significant improvement compared to the GA for two datasets with more attributes.

5 Conclusions

The design of IT3FS using an SSA is proposed; the optimization algorithm determines the configuration of GBell MFs (inputs), constants (output), and the fuzzy rules. To compare with other types of FL, the SSA performs the optimization of T1FS and IT2FS. In the case of IT2FS and IT3FS, additional parameters for the MFs are found, such as $LowerScale$ and $LowerLag$. The optimization algorithm designs fuzzy systems, but their real performance is determined in the testing phase. Analyzing the results achieved by the SSA, we can determine that for all the databases used in this study, the SSA designs IT3FS that allow for a higher accuracy percentage than the other types of FL discussed in this work.

Also, in the testing phase, the SSA managed to obtain better results. Comparing the best results obtained by the SSA with those previously achieved by a GA reveals that the GA outperformed

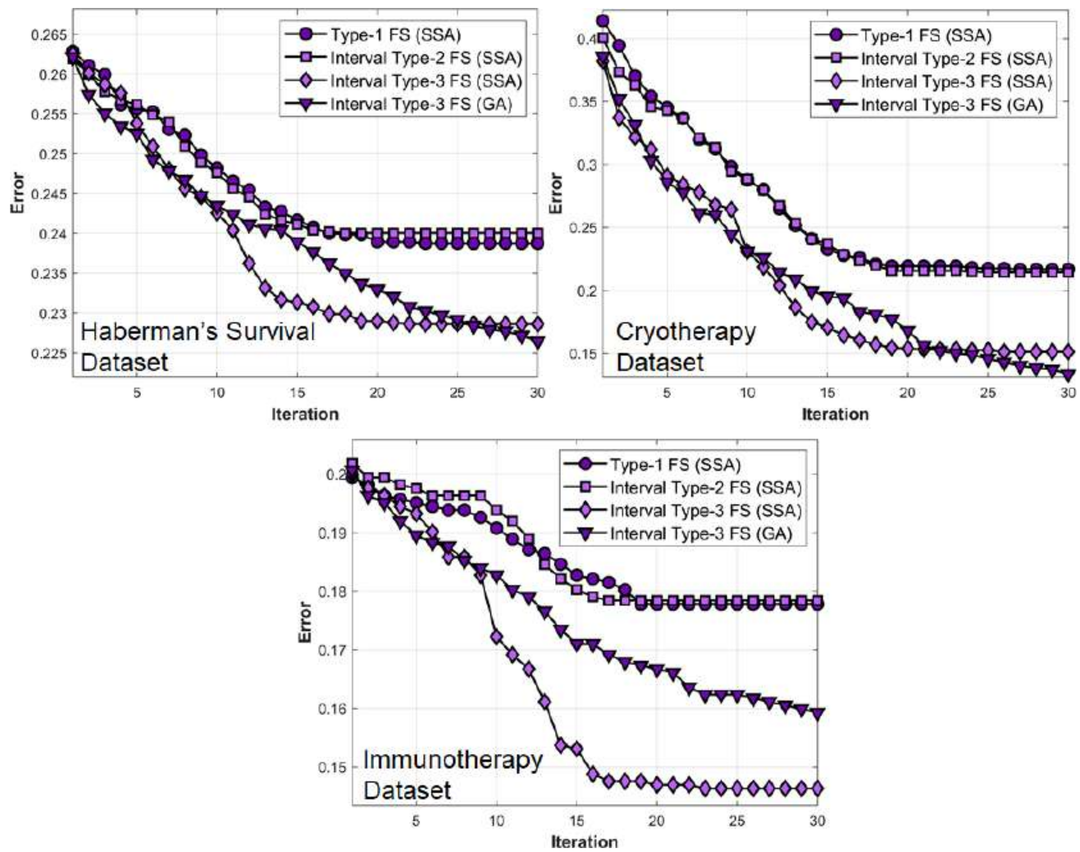

Fig. 7. Average convergence of the different experiments

Table 6. Z-test values for SSA vs GA (IT3FS)

Dataset	Optimization algorithm	Mean	Std Dev	z-Value	p-Value
Haberman's Survival	SSA	76.64	0.9069	0.5954	0.2758
	GA	76.50	0.8699		
Cryotherapy	SSA	89.17	1.9777	2.0235	0.0215
	GA	88.15	1.9208		
Immunotherapy	SSA	84.72	2.7050	1.8608	0.0314
	GA	83.61	1.8382		

it in two databases during the design phase, as evidenced by the average convergence. However, when comparing the behavior in the testing phase, we can see that for the three databases, the best average is obtained by the SSA. In the statistical comparison, we observe that type-3 fuzzy classifiers designed by the SSA exhibit a significant difference in their real behavior, particularly when the databases contain more attributes. As future work, we plan to conduct further comparisons using databases with more attributes and more instances to establish further that IT3FS are more effective when the number of attributes increases, as demonstrated in this study. We will consider other types of applications [34, 14].

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