

Article

Dementia Classification Approach Based on Non-Singleton General Type-2 Fuzzy Reasoning

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Abstract: Dementia is the most critical neurodegenerative disease that gradually destroys memory and other cognitive functions. Therefore, early detection is essential, and to build an effective detection model, it is required to understand its type, symptoms, stages and causes, and diagnosis methodologies. This paper presents a novel approach to classify dementia based on a data set with some relevant patient features. The classification methodology employs non-singleton general type-2 fuzzy sets, non-singleton interval type-2 fuzzy sets, and non-singleton type 1 fuzzy sets. These advanced fuzzy sets are compared with traditional singleton fuzzy sets to evaluate their performance. The Takagi–Sugeno–Kang TSK inference method is used to handle fuzzy reasoning. In the process, the parameters of the membership functions (MFs) and rules are obtained using ANFIS, and non-singleton MFs are optimized with PSO. The results demonstrate that non-singleton general type-2 fuzzy sets improve classification accuracy compared to singleton fuzzy sets, demonstrating their ability to model the uncertainties inherent in the diagnosis of dementia. This improvement suggests that non-singleton fuzzy systems offer a more robust framework for developing effective diagnostic tools in the medical domain. Accurate classification of dementia is of utmost importance to improve patient care and advance medical research.

Keywords: non-singleton fuzzy sets; non-singleton general type-2 TSK fuzzy logic; type-2 fuzzy models for dementia; fuzzy classification

MSC: 03B52; 68T27; 68T37; 94D05



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1. Introduction

In the field of artificial intelligence (AI) and intelligent computing, fuzzy systems have emerged as a critical area of research and application. Fuzzy systems, which are based on the principles of fuzzy logic introduced by Lotfi Zadeh [1], provide a powerful framework for modeling and reasoning under uncertainty. This capability is particularly valuable in the medical domain, where data can often be ambiguous and imprecise. Traditional type-1 fuzzy systems have been widely used in various applications; however, type-2 fuzzy systems offer an enhanced ability to handle higher degrees of uncertainty [2–6], making them highly suitable for complex medical diagnostics. Type-2 fuzzy systems, and particularly non-singleton type-2 fuzzy systems, provide additional flexibility and robustness in modeling uncertainty [7–9]. Unlike singleton fuzzy sets that use crisp values, non-singleton fuzzy sets consider a range of possible membership values, allowing for a more nuanced representation of input uncertainties. This distinction is crucial in medical diagnostics, where variability in patient data can significantly impact the accuracy of classification models. Furthermore, in the fuzzy inference systems, the Sugeno method offers several advantages over the Mamdani approach. Developed by Takagi, Sugeno, and Kang (TSK), the Sugeno inference method utilizes linear or constant functions in the consequent part of the rules, resulting in improved computational efficiency and easier integration with optimization techniques [10]. This makes Sugeno fuzzy systems particularly well-suited for applications requiring precise and real-time decision-making.

Dementia is a growing global health challenge that affects millions of individuals and their families. The World Health Organization (WHO) estimates that around 50 million people worldwide are living with dementia, with nearly 10 million new cases diagnosed each year [11]. This progressive neurological disorder not only impairs cognitive functions such as memory and reasoning but also significantly impacts daily living activities and overall quality of life. The escalating prevalence of dementia necessitates the development of advanced diagnostic tools to facilitate early detection and management, thereby improving the standard of living of patients and easing the social and family burden. This research aims to contribute to the development of more accurate and reliable diagnostic tools for dementia, ultimately enhancing patient care and supporting the global effort to combat this debilitating condition.

This paper presents a novel approach to dementia classification using advanced non-singleton general type-2 fuzzy sets. The Takagi–Sugeno–Kang inference method is employed to handle the fuzzy reasoning process. Specifically, the approach consists of developing and comparing models based on non-singleton TSK general type-2 fuzzy inference systems (NSTSKGT2FIS), non-singleton TSK interval type-2 inference systems (NSTSKIT2FIS), and non-singleton TSK type-1 fuzzy inference systems (NSTSKT1FIS). These models are evaluated against traditional singleton fuzzy sets to assess their effectiveness in improving classification accuracy. The main challenge in the development of fuzzy systems lies in the parameterization of the models. For this study, the parameters, rules, and the number of membership functions MFs for the type-1 fuzzy system inputs were initially determined using the Adaptive Neuro-Fuzzy Inference System (ANFIS) [12]. These parameters served as the basis for generating the parameters for the interval and general type-2 fuzzy systems, specifically to variate the footprint of uncertainty FOU in the membership functions of these systems. Another significant challenge in non-singleton fuzzy systems is the generation and parameterization of the non-singleton membership functions for the three systems NSTSKGT2FIS, NSTSKIT2FIS, and NSTSKT1FIS; in the proposal, the non-singleton is optimized using the PSO algorithm, whose strategy is explained in Section 4. The study aims to demonstrate the superiority of non-singleton fuzzy sets in capturing the inherent uncertainties in medical data, thereby enhancing the accuracy and reliability of dementia classification models.

The remainder of this paper is structured as follows: Section 2 presents a general review of non-singleton fuzzy sets. Section 3 provides a comprehensive review of related work in the application of fuzzy systems in medical diagnostics. Section 4 details the methodology employed in developing the fuzzy classification models, including the dataset description. Section 5 presents the results of the comparative analysis between different fuzzy sets. Section 6 discusses the findings and results. Finally, Section 7 concludes the paper with recommendations for future research directions in this area.

2. Non-Singleton Fuzzy Sets

A Non-Singleton Fuzzy Inference System (NSFIS) is a type of fuzzy inference system where both the inputs and the outputs are represented as fuzzy sets. Unlike singleton fuzzy inference systems, which use crisp values for the output of each rule, NSFISs maintain a fuzzy nature throughout the process. This allows for more detailed modeling of complex systems. Some disadvantages include that they are more complex to design, implement, and understand; compared to singleton FIS, they are slower and require more computational resources [7–9].

Non-Singleton Fuzzy Inference Systems have found applications in various fields due to their ability to handle uncertainty and model complex systems. Here are some notable areas and examples where NSFISs are implemented. In the area of control systems, they have been used in adaptive control to handle uncertainties in processes such as robotic control and industrial automation. In [13], an optimized type-2 NSFIS is presented to control the velocities and pair forces for autonomous mobile robots. In [14], a hybrid learning method is presented, where T1 and IT2 FIS are implemented; these were applied

for the modeling and prediction of the transfer bar surface temperature in an industrial hot strip mill facility achieving favorable results. In [15], a comparative analysis of NST1FIS and singleton IT2FIS controllers for a nonlinear servo system is provided. Experimental simulation results were carried out to assess the effect of increasing levels of uncertainty, introduced as input noise, and to evaluate the effectiveness of each FLC in managing this uncertainty.

In the area of image preprocessing, Ref. [16] introduced a method for eliminating mixed Gaussian and impulse noise from images using a non-singleton IT2FIS. This method also incorporates a quantum-behaved Particle Swarm Optimization algorithm to optimize the FIS parameters.

NSFISs are applied in the prediction of chaotic time series as well. In [17], NSFISs were used in prediction experiments with the Mackey–Glass and Lorenz time series. The findings reveal that the proposed adaptive NSFIS framework provides significant benefits, particularly in environments with high noise level variations, which are common in real-world scenarios.

In the field of medical diagnosis and healthcare, Ref. [18] examined a non-singleton fuzzy logic classifier, optimized via a Genetic Algorithm (GA), for a benchmark cardiac arrhythmias classification problem. The results show that the non-singleton fuzzy logic classifier achieved high classification accuracy by utilizing features that are easier to extract but contain higher uncertainties.

In [19], a significant contribution is made by introducing a novel approach for flowmeter fault detection using optimized non-singleton type-3 fuzzy logic systems (FLSs). This method is applied in an experimental gas industry plant, where it is tested on different types of flowmeters, and the impact of common faults is analyzed. The findings show that this new approach can detect a range of faults with greater accuracy than traditional methods. In [20], a new technique is developed that utilizes type-3 fuzzy logic systems (T3-FLS) with non-singleton fuzzification to model and predict CO₂ solubility.

Recent research in non-singleton fuzzy inference systems (NSFISs) focuses on enhancing efficiency and accuracy through optimization techniques and hybrid systems. In [13] and [21], genetic algorithms are integrated to tune the parameters of type-2 NSFISs, while in [22], a multiobjective evolutionary algorithm (MOEA) is implemented to optimize both non-singleton type-1 and singleton IT2 FIS. Additionally, Ref. [21] proposed combining NSFISs with other machine learning techniques, such as neural networks and support vector machines, to further improve their performance.

Non-Singleton Fuzzy Inference Systems provide a powerful framework for modeling and decision-making in systems characterized by uncertainty and complexity. Their applications span across various domains, demonstrating their versatility and effectiveness in handling real-world problems.

3. State of the Art of Fuzzy Logic-Based Systems in Dementia Diagnosis

In recent years, artificial intelligence (AI) techniques have been applied across various domains, including the medical field, to enhance performance and efficiency in a wide range of tasks. Expert systems developed using soft computing techniques, such as artificial neural networks, fuzzy logic, and genetic algorithms, assist medical practitioners in diagnosing diseases more effectively. However, these techniques have limitations when working with uncertain and multidimensional data.

Fuzzy logic is widely used in the area of healthcare systems, particularly in scenarios where the doctor-to-patient ratio is small, and resources are limited [23,24]. These systems can act as valuable tools for specialists, aiding in diagnosis and decision-making processes. This section focuses on various fuzzy models used in the diagnosis of dementia, including Alzheimer's disease.

In relation to the fuzzy estimation and classification of dementia, in [25], a fuzzy estimation system was applied to detect the level of dementia by monitoring participants' sleep using air pressure and ultrasonic sensors. The fuzzy model estimated dementia

severity through a set of rules, demonstrating the potential of fuzzy logic in continuous and non-invasive monitoring. In [26], the authors proposed a system to classify the degree of dementia using fuzzy logic. The parameters of the system were adjusted using evolutionary algorithms, and the model was implemented in a robot for dementia therapy. Evaluated through a test person study, the system achieved favorable results, highlighting the adaptability of fuzzy logic in robotic applications for medical therapy.

In the Alzheimer's disease prediction, Ref. [27] presented an evaluation of a hybrid neuro-fuzzy system (NFS) for diagnosing Alzheimer's disease which showed improved Root Mean Square Error (RMSE) and F-Score compared to well-known approaches; this highlights the advantage of combining neural networks and fuzzy logic to enhance diagnostic accuracy. In [28], a method utilizing fuzzy logic was developed for identifying and classifying Alzheimer's disease (AD) using 3D MRI brain images. This study aimed to demonstrate the effectiveness of fuzzy logic in managing complex imaging data for early diagnosis of AD. In [29], a hybrid approach combining optimized deep fuzzy clustering and segmentation with a Deep Maxout Network was introduced for classifying AD. The segmented images were analyzed using a Deep Fuzzy Clustering algorithm, with parameters fine-tuned by the Sea Lion Deer Hunting Optimization (SLDHO) algorithm. This method achieved enhanced performance, with specificity, sensitivity, and accuracy reaching 89.8%, 84.4%, and 87.4%, respectively.

In another study [30], an FIS employing the subtractive clustering algorithm was used to classify MRI images of patients with Mild Cognitive Impairment (MCI) or AD compared to Normal Controls (NCs). By utilizing features such as mean values and standard deviations from specific brain regions, the system achieved an overall performance with 86% sensitivity, 91% specificity, 88% accuracy, and 88% positive predictive value for distinguishing AD from normal classification.

In [31], a fuzzy logic-based method was designed to evaluate independence and safety in patients with AD. The Ubiksim platform was utilized to simulate complex social behaviors, with the system adjusting membership functions according to the monitoring environment based on the fuzzy logic model.

For cognitive stimulation therapy, Ref. [32] introduced a fuzzy adaptive cognitive stimulation therapy system aimed at Alzheimer's patients. This game-based system assessed the performance of patients during interactions and provided an auto-adaptive therapeutic approach, thereby reducing the need for therapist involvement in assessment and planning.

The combination of deep learning (DL) with fuzzy logic was investigated in [33], where a model was proposed that integrates deep learning for feature extraction with a fuzzy hyper-plane-based least square twin support vector machine (FLS-TWSVM) for classification. This model achieved high accuracy in classifying different stages of AD using MRI images, highlighting the effective synergy between DL and fuzzy systems.

In relation to Intuitionistic Fuzzy Systems, Ref. [34] applied an intuitionistic fuzzy least square twin support vector machine (IFLSTSVM) to tackle class imbalance issues in the diagnosis of AD and breast cancer. This approach demonstrated superior performance over baseline models, particularly in managing noisy data and addressing class imbalance problems.

Regarding type-2 fuzzy logic systems, in [35], the authors introduced an integration of the Internet of Medical Things (IoMT) with the Tsukamoto Type-2 Fuzzy Inference System (TT2FIS) for medical diagnostics. This approach, applied to tuberculosis and Alzheimer's disease, utilized type-2 fuzzy sets to manage data complexities and uncertainties, enhancing diagnostic accuracy.

4. Non-Singleton TSK General Type-2 Fuzzy Reasoning

4.1. Membership Functions Used in the Implementation

In the fuzzification process, the T1, IT2 and GT2 MFs are represented as follows:

1. T1 FIS model is represented with gauss MFs (1), where x is the universe on discourse, σ is the standard deviation, and m the center of the function [36].

$$\mu(x) = \text{gaussMF}(x, [\sigma \ m]) = \exp \left[-\frac{1}{2} \left(\frac{x - m}{\sigma} \right)^2 \right] \quad (1)$$

2. In the case of the implementation of the IT2 FIS, the IT2 Gaussian MF with uncertainty in the mean is implemented. The necessary parameter for an IT2 MF is presented in Equation (2), where x is the universe on discourse, σ is the standard deviation, m_1 is the mean for the upper MF $\bar{\mu}(x)$ (3), and m_2 for the lower MF $\underline{\mu}(x)$ (4). The IT2 MF is illustrated in Figure 1 [37].

$$\tilde{\mu}(x) = \bar{\mu}(x), \underline{\mu}(x) = \text{igaussmtype2}(x, [\sigma \ m_1 \ m_2]) \quad (2)$$

$$\bar{\mu}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - m_1}{\sigma} \right)^2 \right] \quad (3)$$

$$\underline{\mu}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - m_2}{\sigma} \right)^2 \right] \quad (4)$$

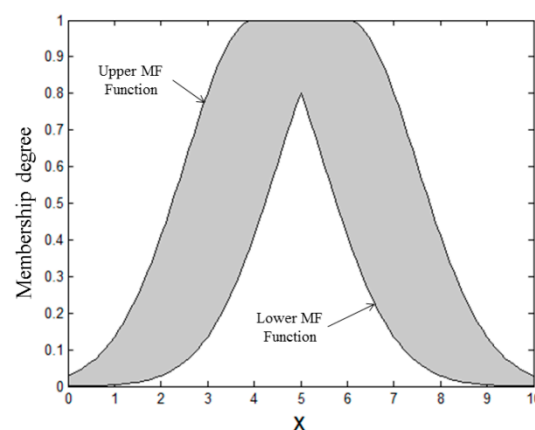


Figure 1. Interval type-2 membership function.

3. GT2 FIS is modeled using Gaussian Primary Membership Function (PMF) with Uncertain Mean and Gaussian Secondary Membership Function (SMF). This GT2 MF, represented as $\tilde{\mu}(x, u)$, is illustrated in Equation (5) in functional form, where “gaussmgausstype2” denotes a Gaussian PMF with an uncertain mean and a Gaussian SMF. It involves four parameters $\{\sigma, m_1, m_2, \rho\}$, where σ is the standard deviation of the PMF, m_1 and m_2 are the left and right means of the Gaussian MF with uncertain mean, and ρ is the fraction of uncertainty that affects the support of the SMF [38]. The GT2 MF is shown in Figure 2.

$$\tilde{\mu}(x, u) = \text{gaussmgausstype2}(x, u, [\sigma, m_1, m_2, \rho]) \quad (5)$$

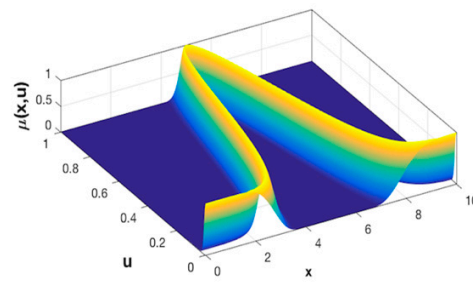


Figure 2. Sample of a “gaussmgaustype2” GT2 MF.

4.2. PSO Configuration to Optimize the Non-Singleton MFs

The classical PSO algorithm [39] is used to optimize the non-singleton T1 MFs for each input of the general approach, after that this is taken as the basis to generate the non-singleton IT2 and GT2 MFs. According to Equation (1), the parameter to be optimized by the PSO is only the m . The particle structure of the PSO consists of nine positions; one for each input of the T1 FIS; Figure 3 presents the structure and Table 1 details the composition of the particle, describing the data that are controlled in each position and the corresponding search space. The value of m takes a different value for each input. The objective function is represented by the classification accuracy returned by the T1 FIS after this is trained and tested. The FIS to be optimized is a non-singleton Sugeno-type system, utilizing the weighted average (wtaver) method for defuzzification. A detailed overview of the input and output variables is provided in Table 2. The parameters used to configure the PSO algorithm are presented in Table 3.

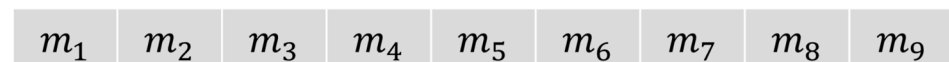


Figure 3. Structure of the particle PSO.

Table 1. Parameters to optimize by PSO.

Point	Min Value	Max Value
m_1	1	10
m_2	1	15
m_3	0	1
m_4	0	1
m_5	1	10
m_6	1	10
m_7	1	10
m_8	1	10
m_9	0	1

Table 2. General structure of the FIS.

No.	Linguistic Variable	Linguistic Values	Range
1	Age	Lowage	[20, 100]
		Middleage	
		Highage	
		X_1	
2	EducationalLevel	LowEducation	[0, 15]
		MiddleEducation	
		HighEducation	
		X_1	

Table 2. Cont.

No.	Linguistic Variable	Linguistic Values	Range
3	HeartRate	LowHeartRate	[0, 100]
		MiddleHeartRate	
		HighHeartRate	
		X_1	
4	AlcoholLevel	LowAlcoholLevel	[0, 1]
		MiddleAlcoholLevel	
		HighAlcoholLevel	
		X_1	
5	Weight	LowWeight	[40, 100]
		MiddleWeight	
		HighWeight	
		X_1	
6	SmokingStatus	LowSmoking	[0, 100]
		MiddleSmoking	
		HighSmoking	
		X_1	
7	DepressionStatus	LowDepresion	[0, 1]
		MiddleDepresion	
		HighDepresion	
		X_1	
8	PhysicalActivity	LowPhysicalAc	[0, 150]
		MiddlePhysicalAc	
		HighPhysicalAc	
		X_1	
9	Diabetic	LowDiabetic	[0, 1]
		MiddleDiabetic	
		HighDiabetic	
		X_1	

Table 3. Parameters used for the PSO algorithm.

PSO Parameters	
Particles (N)	20
Inertial weight (W)	0.85
Iterations	50
Cognitive constant (C1)	2
Social constant (C2)	2

4.3. Non-Singleton TSK General Type-2 Fuzzy Model

The process to model the fuzzy reasoning based on NSTSKT1FIS, NSTSKIT2FIS, and NSTSKGT2FIS is explained as follows.

1. Read the input dataset. Read the dementia disease database defined in Section 4.4 and described in Table 4.

Table 4. Dementia patient health features.

Number	Features Data	Min Value	Max Value
1	Age	60	90
2	EducationLevel	0	15
3	HeartRate	60	100
4	AlcoholLevel	0.000411376	0.19986637
5	Weight	50.0697307	99.9827221
6	SmokingStatus	0	100
7	DepresionStatus	0	1
8	PhysicalActivity	0	150
9	Diabetic	0	1

2. Define the inputs and the output for the NSTSK fuzzy inference system. The NST-SKT1FS, NSTSKIT2FS, and NSTSKGT2FS consist of nine inputs to map the features of the dementia dataset (Age, EducationLevel, HeartRate, AlcoholLevel, Weight, SmokingStatus, DepresionStatus, PhysicalActivity, and Diabetic) and one output (Dementia). To model the three fuzzy systems, the inputs are represented with respective MFs mentioned in Section 4.1; the process to generate the fuzzy models is described as follows:
 - First, the parameters of the T1 fuzzy model are calculated using ANFIS [12]; this derives a FIS with nine inputs, one output, and three fuzzy rules. The nine inputs are granulated in three MFs. This process was executed 30 times to achieve better result accuracy. Once the best FIS is calculated, this is used to find the optimal parameter of the non-singleton MFs based on the configuration presented in Section 4.2. Two (Age and EducationLevel) of the nine inputs (Table 2) with their respective parameters obtained through ANFIS and the non-singleton MFs optimized with PSO are expressed as follows:
 - Age: Customize age granulation depending on the application context. In the healthcare system, the categories that could be introduced are young or early adulthood in the range of 20–40 years, adult or late adulthood (40–60 years), and elderly (60+ years). In this approach, these categories are granulated in three Gaussians membership functions (MFs) with the linguistic variables: “Lowage” (6), “Middleage” (7), “Highage” (8), and the non-singleton “X1” (9). This is illustrated in Figure 4.

$$\mu_{\text{Lowage}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 20.64}{6.9} \right)^2 \right] \quad (6)$$

$$\mu_{\text{Middleage}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 48.04}{5.9} \right)^2 \right] \quad (7)$$

$$\mu_{\text{Highage}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 75.45}{6.3} \right)^2 \right] \quad (8)$$

$$\mu_{\text{X1}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 3.5}{0.5} \right)^2 \right] \quad (9)$$

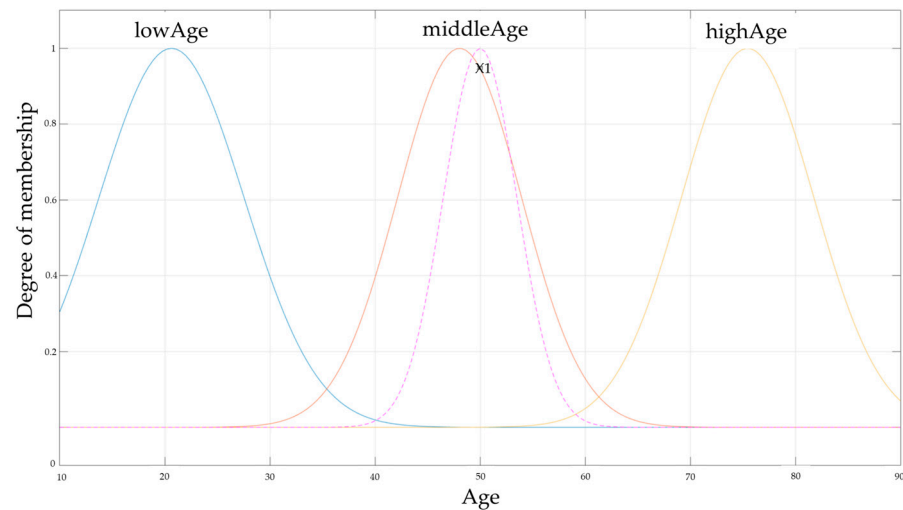


Figure 4. Representation of the T1 MF and the non-singleton for the input age. X1 represents the non-singleton input.

- EducationLevel: “LowEducation” (10), “MiddleEducation” (11), “HighEducation” (12), and the non-singleton “X1” (13).

$$\mu_{\text{LowEducation}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 8.1}{3.2} \right)^2 \right] \quad (10)$$

$$\mu_{\text{MiddleEducation}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 8.25}{2.6} \right)^2 \right] \quad (11)$$

$$\mu_{\text{HighEducation}}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 8.4}{2.9} \right)^2 \right] \quad (12)$$

$$\mu_{X1}(x) = \exp \left[-\frac{1}{2} \left(\frac{x - 10.5}{0.5} \right)^2 \right] \quad (13)$$

- The previous T1 fuzzy model was used as a basis to generate the NSTSKIT2FS and the NSTSKGT2FS.
- In the case of the NSTSKIT2FS model, the challenge is to obtain the FOU for the MFs. In this approach, the FOU factor is calculated with Equations (14) and (15), where f_x is a factor of FOU and this can take a value between 0.2 and 1 with an increment of 0.2, and M is the middle value of the parameters of the MF expressed in Equation (7). Once the value of f_x FOU has been calculated, the next step is parameterizing the IT2 MFs based on the parameter of the T1 MFs (6)–(9) and adding the FOU factor (f_x FOU).

$$f_x = 0.2 \quad (14)$$

$$f_x \text{FOU} = f_x * M \quad (15)$$

- Based on the parameterization of the IT2 MF (2), an example is added as to how it is calculated for μ_{Lowage} (16), $\mu_{\text{Middleage}}$ (17), and μ_{Highage} (18). The numeric values are expressed in Equations (20)–(22) considering a f_x value of 0.2. The non-singleton is expressed in Equations (19) and (23). The input IT2 MF including the non-singleton X1 is illustrated in Figure 5

$$\mu_{\text{Lowage}}(x) = \text{igausstype2}(x, [\sigma \mu_{\text{Lowage}} - f_x \text{FOU} \mu_{\text{Lowage}} + f_x \text{FOU}]) \quad (16)$$

$$\mu_{\text{Middleage}}(x) = \text{igaussmtype2}(x, [\sigma \mu_{\text{Middleage}} - \text{fxFOU} \mu_{\text{Middleage}} + \text{fxFOU}]) \quad (17)$$

$$\mu_{\text{Highage}}(x) = \text{igaussmtype2}(x, [\sigma \mu_{\text{Highage}} - \text{fxFOU} \mu_{\text{Highage}} + \text{fxFOU}]) \quad (18)$$

$$\mu_{X1}(x) = \text{igaussmtype2}(x, [\sigma \mu_{\text{Highage}} - \text{fxFOU} \mu_{\text{Highage}} + \text{fxFOU}]) \quad (19)$$

$$\mu_{\text{Lowage}}(x) = \text{igaussmtype2}(x, [3.2 \ 59.63 \ 89.65]) \quad (20)$$

$$\mu_{\text{Middleage}}(x) = \text{igaussmtype2}(x, [2.6 \ 60.04 \ 90.06]) \quad (21)$$

$$\mu_{\text{Highage}}(x) = \text{igaussmtype2}(x, [2.9 \ 60.44 \ 90.46]) \quad (22)$$

$$\mu_{X1}(x) = \text{igaussmtype2}(x, [0.5 \ 0.5]) \quad (23)$$

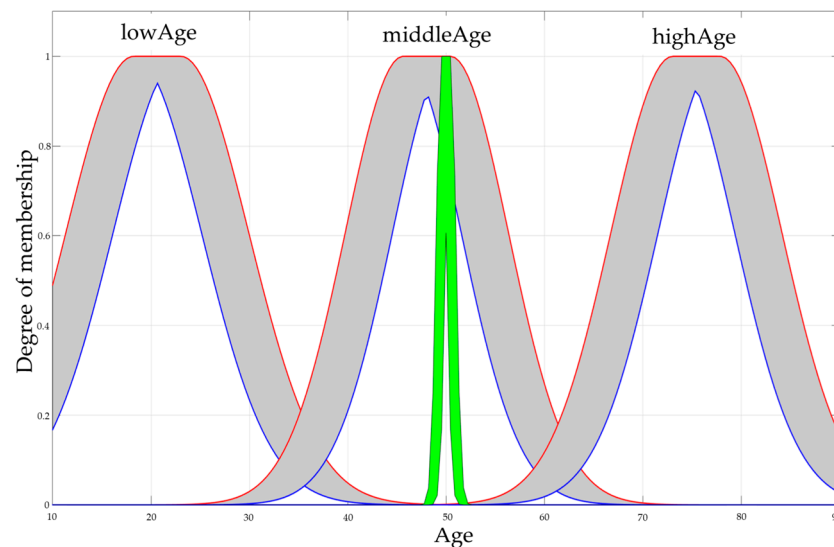


Figure 5. Representation of the IT2 MF and the non-singleton for the input age. The gray ones are the IT2 MFs for the linguistic variables lowAge, middleAge and highAge. Green represents the non-singleton input.

- In the case of the implementation of the NSTSKGT2FS, the optimized T1 was taken as the basis for calculating the parameters of the gaussmgausstype2 (5), it requires four parameters $\{\sigma, m_1, m_2, \rho\}$. In this case, to add the FOU for the PMF, a procedure similar to that for the IT2 MF is used; this is calculated using Equations (14) and (15). The parameter ρ is defined with the value of 0.1; this was determined after several tests and after performing a variation from 0.1 to 1 until the best result was achieved. Based on this parameterization, an example of how GT2 MF is calculated for μ_{Lowage} , $\mu_{\text{Middleage}}$, and μ_{Highage} is expressed in Equations (24)–(26). The numeric values are presented in Equations (28)–(30) considering the factor fx of 0.2 and a value for ρ of 0.1. The non-singleton is expressed in Equations (27) and (31). The input GT2 MF is illustrated in Figure 6.

$$\mu_{\text{Lowage}}(x, u) = \text{gaussmgausstype2}(x, u[\sigma \mu_{\text{Lowage}} - \text{fxFOU} \mu_{\text{Lowage}} + \text{fxFOU} \rho]) \quad (24)$$

$$\mu_{\text{Middleage}}(x, u) = \text{gaussmgausstype2}(x, u[\sigma \mu_{\text{Middleage}} - \text{fxFOU} \mu_{\text{Middleage}} + \text{fxFOU} \rho]) \quad (25)$$

$$\mu_{\text{Highage}}(x, u) = \text{gaussmgausstype2}(x, [\sigma \mu_{\text{Highage}} - \text{fxFOU} \mu_{\text{Highage}} + \text{fxFOU} \rho]) \quad (26)$$

$$\mu_{X1}(x, u) = \text{gaussmgausstype2}(x, [\sigma \mu_{\text{Highage}} - \text{fxFOU} \mu_{\text{Highage}} + \text{fxFOU} \rho]) \quad (27)$$

$$\mu_{\text{Lowage}}(x, u) = \text{gaussmgausstype2}(x, u, [3.2 \ 59.63 \ 89.65 \ 0.1]) \quad (28)$$

$$\mu_{\text{Middleage}}(x) = \text{gaussmgausstype2}(x, u, [2.6 \ 60.04 \ 90.06 \ 0.1]) \quad (29)$$

$$\mu_{\text{Highage}}(x) = \text{gaussmgausstype2}(x, u, [2.9 \ 60.44 \ 90.46 \ 0.1]) \quad (30)$$

$$\mu_{X1}(x) = \text{gaussmgaustype2}(x, u, [1.5 \ 1.5 \ 0.1]) \quad (31)$$

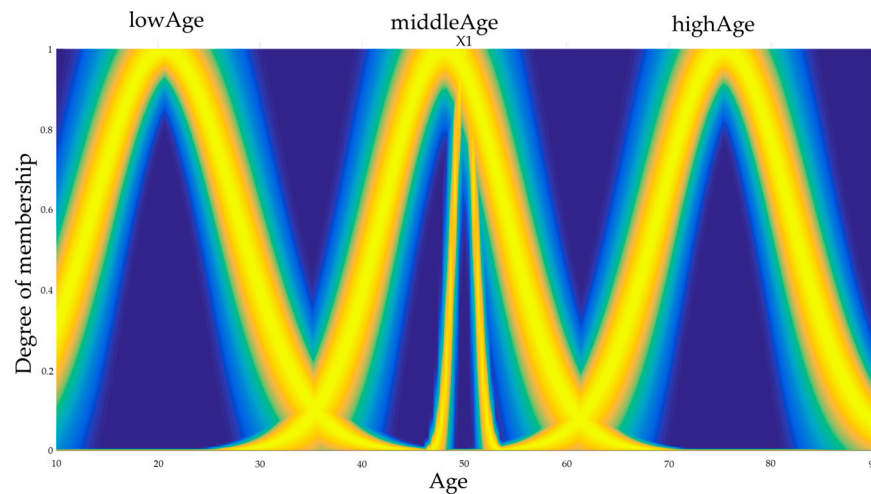


Figure 6. Representation of the GT2 MF and the non-singleton for the input age. X1 represents the non-singleton input.

3. **STK Fuzzy Inference System.** The knowledge base of the three FIS contains three fuzzy rules, which control the input–output relationship of the fuzzy classification model and implement the Takagi–Sugeno style inference engine and a single point in the outputs (constant values). The defuzzification for the IT2 and GT2 FIS is processed with the Center of Sets method and the T1 FIS with the wtaver method.

4.4. Dementia Dataset

Dementia Patient Health. The dataset was obtained from [40] and consists of 1000 patient records, where 9 features were selected. The output target is dementia; it has two values to indicate the presence (1) or absence (0) of dementia. The features and the range value that contain the data set are presented in Table 4 with their minimum and maximum values, respectively.

1. **Age:** The age of the patient is an essential demographic factor.
2. **EducationLevel:** The highest level of education attained by the patient, which may correlate with health literacy.
3. **Heart Rate:** Denotes the number of heart beats per minute, a critical indicator of cardiovascular health.
4. **Alcohol Level:** Measures the alcohol consumption level of patients, possibly reflecting lifestyle choices.
5. **Weight:** The mass of the patient in kilograms, a fundamental measure of health.
6. **SmokingStatus:** Reflects the patient’s smoking habits, an important lifestyle indicator.
7. **DepressionStatus:** Indicates whether the patient has depression, which can be related to cognitive health.
8. **PhysicalActivity:** The level of physical activity of the patient, highlighting lifestyle impacts on health.
9. **Diabetic (Binary):** Indicates whether a patient has been diagnosed with diabetes (1 for yes, 0 for no).

This dataset serves as a rich source for analysis, providing a multifaceted view of factors that may contribute to the onset and progression of dementia. It is a valuable resource for researchers looking to explore the complex interplay between lifestyle, genetics, and health outcomes [40].

5. Results

This section presents a comparative analysis of the results obtained from various fuzzy classification approaches. The analysis includes the experimental outcomes achieved by the singleton TKS model and the non-singleton TKS models for type-1, interval type-2, and general type-2 fuzzy systems. The methodology used to obtain these results is detailed in Section 4.

All experiments were applied to the dementia dataset described in Section 4.3. To evaluate the performance of all fuzzy systems, two experimental segments of the dataset were created. In the first segment, the dataset was split into 70% for training and 30% for testing; while in the second segment, it was divided into 60% for training and 40% for testing.

In the first experiment, the database was processed using singleton TKS and non-singleton TKS T1 FIS. The results are presented in Table 5.

Table 5. Results of using STSKT1 FIS and NSTSKT1 FIS.

Fuzzy Model	Dataset (70-30)			Dataset (60-40)		
	Best	Mean	STD	Best	Mean	STD
STSKT1FIS	0.7967	0.7579	0.0207	0.7975	0.7575	0.0148
NSTSKT1FIS	0.8033	0.7622	0.0213	0.8025	0.7642	0.0165

In the case of the experimentation, using singleton TSK and non-singleton TSK IT2 also, 30 experiments were performed but with a variation in the FOU with a factor from 0.2 to 1 increasing in 0.2. Tables 6 and 7 present the summary of the results.

Table 6. Results of using STSKIT2FIS and NSTSKIT2FIS with 70-30 partition dataset.

FOU	STSKIT2FIS			NSTSKIT2FIS		
	Best	Mean	STD	Best	Mean	STD
0.2	0.8000	0.7554	0.0237	0.8233	0.7661	0.0218
0.4	0.8067	0.7430	0.0231	0.8033	0.7581	0.0201
0.6	0.8033	0.7616	0.0188	0.8100	0.7621	0.0220
0.8	0.8000	0.7537	0.0218	0.7967	0.7591	0.0210
1	0.7967	0.7631	0.0192	0.8100	0.7639	0.0240

Table 7. Results of using STSKIT2FIS and NSTSKIT2FIS with 60-40 partition dataset.

FOU	STSKIT2FIS			NSTSKIT2FIS		
	Best	Mean	STD	Best	Mean	STD
0.2	0.7850	0.7570	0.0149	0.7950	0.7621	0.0153
0.4	0.7875	0.7566	0.0182	0.7925	0.7669	0.0152
0.6	0.8025	0.7623	0.0177	0.8000	0.7605	0.0148
0.8	0.7950	0.7591	0.0159	0.8075	0.7615	0.0204
1	0.7975	0.7565	0.0189	0.8025	0.7750	0.0187

In the case of the singleton TSK and non-singleton TSK GT2 FIS, 30 executions were performed for each variation of the FOM. The best accuracy, mean, and standard deviation are presented in Tables 8 and 9.

Table 8. Results of using STSKGT2FIS and NSTSKGT2FIS with 70-30 partition dataset.

FOU	STSKGT2 FIS			NSTSKGT2 FIS		
	Best	Mean	STD	Best	Mean	STD
0.2	0.8133	0.7657	0.0238	0.8250	0.7678	0.0235
0.4	0.8033	0.7562	0.0223	0.8033	0.7657	0.0220
0.6	0.8033	0.7600	0.0197	0.8067	0.7582	0.0185
0.8	0.7900	0.7600	0.0146	0.7900	0.7598	0.0207
1	0.7800	0.7540	0.0168	0.8000	0.7578	0.0254

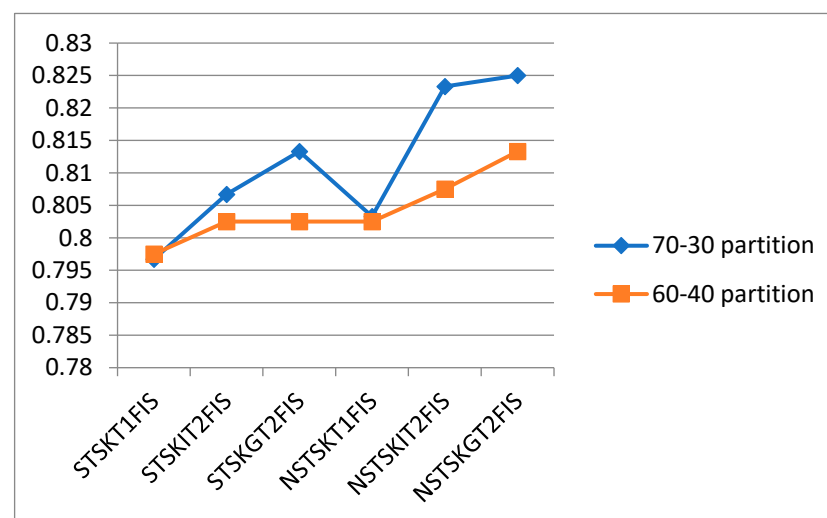
Table 9. Results of using STSKGT2 FIS and NSTSKGT2 FIS with 60-40 partition dataset.

FOU	STSKGT2 FIS			NSTSKGT2 FIS		
	Best	Mean	STD	Best	Mean	STD
0.2	0.7975	0.7591	0.0207	0.8025	0.7588	0.0170
0.4	0.8025	0.7623	0.0187	0.8133	0.7657	0.0170
0.6	0.7825	0.7587	0.0147	0.8025	0.7667	0.0189
0.8	0.7775	0.7587	0.0100	0.7950	0.7628	0.0152
1	0.7925	0.7601	0.0161	0.7900	0.7590	0.0197

A summary of the best classification accuracy for the dementia dataset using singleton TSK and non-singleton TSK FIS is presented in Table 10, and the differences are illustrated in Figure 7.

Table 10. Results of the best classification accuracy.

Model	Best	
	70-30 Partition	60-40 Partition
STSKT1FIS	0.7967	0.7975
STSKIT2FIS	0.8067	0.8025
STSKGT2FIS	0.8133	0.8025
NSTSKT1FIS	0.8033	0.8025
NSTSKIT2FIS	0.8233	0.8075
NSTSKGT2FIS	0.8250	0.8133


Figure 7. Representation of the best classification accuracy.

6. Discussion

According to the results presented in Section 5, it is evident that non-singleton fuzzy systems generally achieve better classification accuracy compared to their singleton counterparts. Specifically, the non-singleton type-1 fuzzy inference system (NSTSKT1FIS) outperformed the singleton type-1 system, achieving a precision value of 0.8033 and 0.8025 for the different segmented data. Similarly, for the non-singleton interval type-2 fuzzy inference system (NSTSKIT2FIS), the non-singleton approach demonstrated superior performance with an accuracy of 0.8233 and 0.8075, compared to 0.8067 and 0.8025 for the singleton system. The non-singleton general type-2 fuzzy inference system (NSTSKGT2FIS) also exhibited improved accuracy over the singleton GT2 FIS, with a value of 0.8250 and 0.8133.

The summary in Table 10 and Figure 7 clearly shows that the best performance was achieved by the NSTSKGT2FIS, surpassing both the NSTSKIT2FIS and the NSTSKT1FIS. This highlights the efficacy of the general type-2 fuzzy sets in capturing and modeling the complex uncertainties present in the data.

When comparing only the singleton systems, the interval type-2 fuzzy inference system (STSKIT2FIS) improved upon the type-1 system (STSKT1FIS), as expected. Furthermore, the general type-2 fuzzy inference system (STSKGT2FIS) performed better than the interval type-2 system. These findings reinforce the notion that higher-order fuzzy systems, such as IT2 and GT2, are inherently better suited for modeling complex systems due to their ability to handle greater levels of uncertainty.

The natural advantage of GT2 FIS lies in its capacity to model more intricate systems by addressing higher levels of uncertainty. The inclusion of non-singleton characteristics enhances this capability further by covering a broader range of uncertainty. This is clearly demonstrated in the results presented in Table 10, where the NSTSKGT2FIS achieved the highest classification accuracy among all tested systems. The improvement in accuracy observed with non-singleton systems can be attributed to their ability to consider a range of possible membership values, rather than relying on single crisp points. This allows for a more detailed and flexible representation of the uncertainties present in the input data, leading to more accurate and reliable classification outcomes.

In summary, the results highlight the superiority of non-singleton fuzzy systems, particularly the NSTSKGT2FIS, in classifying dementia with higher accuracy. The findings suggest that leveraging the advanced modeling capabilities of general type-2 fuzzy sets, combined with non-singleton characteristics, can significantly enhance the performance of fuzzy inference systems in medical diagnostics. This research underscores the importance of adopting sophisticated fuzzy systems to address the complexities and uncertainties inherent in medical data, ultimately contributing to more effective and accurate diagnostic tools.

7. Conclusions

In this paper, we presented three approaches for the classification of dementia using non-singleton Takagi–Sugeno–Kang (TSK) fuzzy systems, including non-singleton type-1 (T1), non-singleton interval type-2 (IT2), and non-singleton general type-2 (GT2) fuzzy sets. The comparative analysis revealed that the non-singleton approaches outperformed their singleton counterparts, highlighting the effectiveness of non-singleton fuzzy systems in handling the inherent uncertainties in medical data.

The implementation of GT2 fuzzy sets offers significant advantages due to their superior ability to model higher degrees of uncertainty and capture more complex relationships within the data. This flexibility is critical in medical diagnostics, where variability and ambiguity are common. Non-singleton fuzzy systems, in general, provide a more comprehensive framework for uncertainty modeling compared to singleton systems, resulting in improved classification accuracy and reliability.

The parameters of the fuzzy systems in this study were optimized using the Adaptive Neuro-Fuzzy Inference System (ANFIS). However, future research could explore optimizing these systems with other advanced algorithms such as genetic algorithms, particle swarm optimization, or ant colony optimization to further improve performance. The

optimization process should include a broader range of membership functions and fuzzy rules. Expanding the dataset with additional features could also enhance the robustness and accuracy of the classification models. Moreover, validating the results with medical experts is essential to ensure the predictions align with clinical standards. Expert input can also help generate a knowledge base of fuzzy rules, making the system more reliable. Another key direction is the development of hybrid systems, which combine the strengths of classification techniques, such as neural networks, with fuzzy logic. Finally, advances in type 3 fuzzy sets are very promising in the management of uncertainty and offer a valuable avenue for future research, which is why it is another methodology that could be considered.

Developing fuzzy classification systems for dementia analysis is crucial in the medical field. Such systems provide valuable tools for early detection and management of dementia, ultimately improving patient outcomes and reducing the burden on healthcare systems. By leveraging the strengths of non-singleton fuzzy systems and the TSK inference method, this research contributes to the advancement of AI-based diagnostic tools, offering promising directions for future research and application in medical diagnostics.

In summary, the study highlights the potential of non-singleton fuzzy systems, particularly GT2 fuzzy sets, in enhancing the classification accuracy of dementia. The findings underscore the importance of optimizing fuzzy systems and expanding datasets to create more effective diagnostic tools, thereby supporting the ongoing efforts to improve healthcare delivery and patient care in the realm of dementia.

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