ISSN 2007-9737

Fuzzy Rule-based Systems and Artificial Intelligence in Medical Applications

Jacinto González-Aguilar, Oscar Castillo, Prometeo Cortés-Antonio*

Tijuana Institute of Technology/TecNM,
Mexico

{D25210011, prometeo.cortes}@tectijuana.edu.mx, ocastillo@tectijuana.mx

Abstract. This article presents a study on technological development, research, and current techniques in artificial intelligence and robotics using rule-based systems focused on medical applications in various medical areas. It analyzes various control techniques, image and signal analysis, and vision control as tools in medical applications by describing knowledge-based systems described by human experts or data that go beyond traditional Boolean logic. These are fundamental in artificial intelligence, especially in complex and high-risk areas such as medicine, for managing uncertainty and modeling expert knowledge. Applications ranging from aspects of preventive, non-invasive, and invasive medicine and healthcare will be reviewed, as well as the methods used in artificial intelligence, such as data analysis models, recognition, monitoring, and medical robotics, which improve the accuracy and safety of procedures. In order to observe the current trend in publications on type-1 and type-2 fuzzy logic controllers used in various medical fields, we have included a summary of the findings from the Medline database.

Keywords. Fuzzy logic control, artificial intelligence, robotics, rule based systems.

1 Introduction

In order for technological systems to simulate the ambiguity and uncertainty of the real world and reason similarly to humans, fuzzy logic is still vital in the twenty-first century. Fuzzy logic is a branch of mathematical logic and was initiated in 1965. (Zadeh, Fuzzy sets 1965), (Zadeh, Outline of a new approach to the analysis of complex systems and decision processes 1973), (Braae 1977) by Lotfi A. Zadeh, professor of computer science at the University of California, Berkeley. A multivalent logic called fuzzy logic (FL) permits intermediate values like high, low, medium, very high, etc. to be defined. Notions such as "quite fast" or "very fast" can be formulated mathematically and processed by computers, with the aim of applying a more human way of thinking to computer programming (Zadeh, Making computers think like people [fuzzy set theory] 1984).

Zadeh always believed that mathematics held the answers to almost all problems, but he realized that classical mathematics had limitations because it did not know how to deal with imprecision. Zadeh used the model of human reasoning, which is remarkably capable of making judgments based on incomplete and imperfect information.

The main objective of FL is to formalize the human ability to reason. Humans naturally apply fuzzy logic to decision-making by handling imprecise data and weighing the value of each element. Zadeh's contribution has been to establish the foundations of fuzzy logic and translate it into decision-making by computers and systems.

The achievements of Aristotle and the philosophers who came before him are largely responsible for the accuracy of mathematics. They proposed the so-called "laws of thought" in an attempt to create a succinct theory of logic and then mathematics (Korner 1967).

In the field of medicine, uncertainty is often encountered: this patient presents a set of signs and symptoms, what disease does he have? The

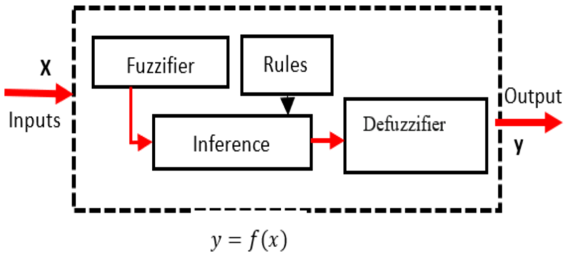

Fig. 1. Type-1 Fuzzy System

degree of uncertainty involved is not always apparent. However, it is known that the relationship between signs and symptoms and the diseases that cause them is variable (there are patients with the same symptoms and different diseases). Fuzzy logic in medicine allows us to work with uncertainty (Hellmann 2001).

This work's primary contribution is to demonstrate the significance of FL in the field of medicine and the annual publications.

The structure of this text is as follows: Section 2 outlines the key elements of a rule-based fuzzy system. A study of Type-1 and Type-2 FL control is presented in Section 3, the literature on fuzzy logic in the medical area is reviewed in Section 4, and the work's conclusions are presented in Section 5.

2 Rule-based Systems

Type-1 fuzzy systems (T1-FS) are currently a very important field of research, both for their mathematical and theoretical applications and for their practical applications. Because they are made up of "IF-THEN" rules whose antecedents and consequents are made up of fuzzy logic instructions rather than classical logic (true/false) instructions, systems based on fuzzy rules are an extension of classical rule-based systems (true/false).

These fuzzy rule-based systems are used as effective tools in applications with different types of uncertainty. The knowledge base in a Type-1 fuzzy system (T1 FS) is formed by defining "IF-THEN" linguistic rules (rule base) and specifying membership functions for each linguistic term (data base). (Fernández, Velasco and López-Carmona 2010). As a result, as seen in Figure 1, we provide a succinct explanation of the elements of the Type-1 fuzzy system (rules, fuzzifier, inference, and defuzzifier) in this section.

2.1 Linguistic Variables

Following their establishment, the rules or variables in the fuzzy system can be viewed as a correspondence between inputs and outputs (the red path in Figure 1), which can be quantitatively stated as y=f(x). A fuzzy system's rules are derived from particular domain data or supplied by one or more subject-matter experts.

A membership function that gives each numerical value a degree between 0 and 1 a measure of how much a value belongs to a set defines fuzzy sets. Linguistic variables are values that are not expressed with an exact number, but with linguistic words or labels such as "low," "moderate," or "high."

2.2 Inference

The process by which a fuzzy logic system draws inferences or choices from imprecise or ambiguous input values and fuzzy rules is known as fuzzy inference. In other words, it mimics the way humans' reason when something is not entirely true or false, but "more or less true." As shown in this example of assisted medical diagnosis, if the fever is high and the pulse is fast, then a serious infection is possible; if the fever is moderate, then a mild infection is possible.

2.3 Fuzzifier

The initial phase of an FL system is called the fuzzifier. Its function is to convert numerical or precise (crisp) values, such as temperature, pressure, or glucose level, into fuzzy values, that is, into degrees of membership in certain linguistic sets such as low, medium, or high. It translates real medical data into linguistic terms that the fuzzy system can process.

2.4 Defuzzifier

The last step in a fuzzy system is the defuzzifier. It converts a fuzzy value the result of inference into a crisp or numerical value that can be used in practice (for example, for dosing medication or displaying an output).

3 Type-2 Fuzzy Logic

As an extension of Type-1 FL (which Lotfi Zadeh proposed in 1965), Type-2 FL was first presented by Lotfi Zadeh in 1975 with the goal of more accurately modeling uncertainty and imprecision. It is a tool that contains a set of mathematical concepts and methodologies for handling the implicit uncertainty contained in fuzzy sets that describe the linguistic values of fuzzy variables. The ideas found in rule-based fuzzy systems can be more accurately modeled by Type-2 fuzzy systems (T2-FS), which are a generalization of traditional Type-1 fuzzy systems.

A tuple defines a Type-2 fuzzy set $\tilde{A}$ in the following way:

$$\tilde{A} = \left\{ \begin{matrix} ((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \\ \forall\, u \in J_x \subseteq [0,1], 0 \leq \mu_{\tilde{A}}(x,u) \leq 1 \end{matrix} \right\}, \quad (1)$$

where u is a member of the interval known as the primary membership and X is the fuzzy variable's domain. that is $u \in J_x \subseteq [0,1]$, $\mu_{\tilde{A}}(x,u)$ is a 2-dimension membership function for defining the secondary membership (Gaxiola, Melin, et al., Interval type-2 fuzzy weight adjustment for backpropagation neural networks with application in time series prediction 2014, Gaxiola, Melin, et al., Optimization of type-2 fuzzy weights in backpropagation learning for neural networks using GAs and PSO 2016, Mendel 2019, Wu and Mendel 2018). If $\mu_{\tilde{A}}(x,u) = 1$for all (x,u) in a fuzzy set then the Type-2 fuzzy set is called interval type-2 fuzzy set (Valdez, et al. 2020, Castro, Castillo and Martinez 2007).

In a Mamdani fuzzy system, a fuzzy rule l can often be written as follows:

$$R^l: if\, x_1\ is\ F_1^l\ and\ x_2\ F_2^l\ then\ y^l = G^l\,. \quad (2)$$

The fuzzy system is Type-2 if one or more of the fuzzy sets in the rule are Type-2.

The fundamental elements of a Type-2 fuzzy system are depicted in Figure 2. Equation 2 can be used to define the collection of fuzzy rules found in the rule block.

The rules are processed within the inference block. The inference step creates an induced type-

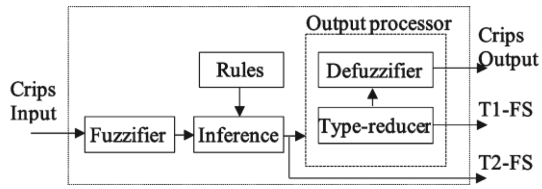

Fig. 2. Type-1 Fuzzy System

2 fuzzy set by processing the rules using type-2 fuzzy set mathematics. Lastly, as illustrated in Figure 2, the induced type-2 fuzzy set can be quantified to translate it to a type-1 fuzzy set or a crisp value in the output processor.

4 Application on Fuzzy Logic in Medicine

As mentioned above, fuzzy logic has numerous applications in different areas of medicine, including decision support systems (Navin, Krishnan and others 2024, Gupta, et al. 2024, Berkhout, Smit and Versendaal 2024), medical image processing (Abdulbaqi, et al. 2024, Yadav, Singh and Yadav 2024), patient monitoring. (pour, et al. 2024), Personalization of medical treatments (Locatelli, et al. 2024), medical risk assessment (Drnovšek, et al. 2025), diagnosis of diseases such as cancer and diabetes, etc.

An overview of FL applications in the medical profession is provided in this section.

4.1 Blood Glucose Control and Monitoring

The principal sugar in the bloodstream and the body's main energy source is blood glucose, sometimes referred to as blood sugar.

It comes mainly from carbohydrate-rich foods and is transported to cells for use, while hormones such as insulin help regulate its levels.

Blood glucose control involves managing sugar levels through diet, exercise, and medication, while monitoring is the process of regularly checking those levels to understand patterns and prevent health problems.

Type-1 fuzzy logic controller system for automating blood glucose regulation. (Mauseth, et al. 2013) (Ibbini 2006) (Almutoory and Almutoory 2025), type-2 diffuse system (Elhoushy, et al. 2024) (Nasar, Jaradat and Rhomdane 2024).

4.2 Anesthesia

Anesthesia is a state of temporary loss of sensation and consciousness induced for medical purposes to prevent pain during procedures like surgery. It can involve analgesia (pain relief), amnesia (memory loss), muscle paralysis, and unconsciousness.

Common types include general anesthesia (for major procedures, causing deep sleep), regional anesthesia (numbing a large part of the body), and local anesthesia (numbing a small area).

Intelligent anesthesia monitoring system based on fuzzy logic (Al-Araji, Dagher and Abdullah 2024) to improve the diagnostic alarm system developed to detect critical events during anesthesia and accurately diagnose hypovolemia in anesthetized patients (Rahim, Deshpande and Hosseini 2007).

Fuzzy expert system for fluid management in general anesthesia: a fuzzy expert system was developed for fluid management in general anesthesia (Baig, Gholamhosseini and Harrison 2012), monitoring systems using Type-2 fuzzy logic (Wei, et al. 2020), (El-Nagar and El-Bardini 2014).

4.3 Diabetes

High blood glucose (or blood sugar) levels are a hallmark of diabetes, a chronic metabolic disease that over time causes major harm to the heart, blood vessels, eyes, kidneys, and nerves. The most prevalent kind is type 2 diabetes, which often affects adults and is caused by insufficient or resistant insulin production. In nations of all income levels, the prevalence of type 2 diabetes has sharply climbed during the previous three decades. Type 1 diabetes is a chronic illness in which the pancreas generates little or no insulin on its own. It is sometimes referred to as juvenile diabetes or insulin-dependent diabetes. Access to reasonably priced therapy, such as insulin, is essential to the survival of those with diabetes. Stopping the rise in diabetes is a worldwide priority.

Support system for the diagnosis of diabetes mellitus using fuzzy logic rules, so that anyone can make an early diagnosis and begin treatment immediately (Niswati, Mustika and Paramita 2018, Ali, Sadi and Goni 2024), classification of diabetic retinopathy (Cordero-Martínez, Sánchez and Melin 2024), Diffuse systems to minimize high glucose spikes and prevent hypoglycemia (Atlas, et al. 2010). Real-Time Glucose Level Interpretation Using a Fuzzy Logic Framework for Diabetes Management (Almutoory and Almutoory 2025).

4.4 Computer Vision in Medicine

Advances in computer vision techniques, particularly those using fuzzy rule-based models, have a significant impact on the medical field.

The following articles propose a GA-based fuzzy system for CAD schemes in disease classification (Tsai, et al. 2004), computer vision algorithm that allows images of healthy retinas to be classified against images with diabetic retinopathy (Ahmadi, et al. 2021), COVID-19 detection from chest X-rays and computed tomography scans. (Banerjee, et al. 2022), breast cancer diagnosis (Alsheikhy, et al. 2022), detection of pneumonia from chest X-ray images (Wu and Mendel 2018), processing magnetic resonance images for the analysis of blood vessels (Hernández-Delgado, et al. 2019), Image segmentation based on fuzzy logic, together with a modified deep learning model, is proposed for skin cancer detection (Singh, Abolghasemi and Anisi 2023), analysis of abdominal computed tomography images for automatic liver cancer diagnosis using image processing algorithm (Khan and Narejo 2019).

4.5 Robotics in medicine

In the medical field, robots are crucial. Thanks to them, less invasive surgical techniques have been implemented, allowing surgeries to be performed in less time. Below is a list of robots used in the field of medicine: autonomous nursing robot. (Narayanan, et al. 2022), robots and smart medical devices in the intensive care unit (Kosa, et al. 2023), robotic surgery (Ragu and Swathi Sri 2022), intelligent dental robot using fuzzy logic (Mago, et al. 2011) (Hashem, Mohammed and Youssef 2020), Assistive robot for patient rehabilitation (Bouteraa, et al. 2020) , help patients with disabilities or lesions to recover mobility and strength in their limbs, minimally invasive surgical robot (Sang, et al. 2016) these robots allow surgeons to perform operations with greater

ISSN 2007-9737

precision and less invasion for the patient, where fuzzy logic is used to control the stability and precision of the robot's movements during surgery, medical diagnostic robot (Huang, Zhu and Tang 2017).

4.6 Cancer

The term "cancer" is used to describe a wide range of illnesses that can start in nearly any organ or tissue in the body when aberrant cells grow out of control, surpass their boundaries, infect nearby body parts, and/or spread to other organs. Lung, the most prevalent cancers in men, and breast, colorectal, lung, cervical, and thyroid cancer are the most common in women. Every year, hundreds of people lose their lives to cancer as a result of inadequate medical resources and poor use of those that are available. Treatment for cancer will be more effective if it is detected early. Chemotherapy, radiation therapy, and/or surgery may be used to treat the majority of malignancies. Fuzzy rules can be used to process pertinent data from cancer cases in order to offer a risk prognosis that can be qualitatively compared to that of an expert. Neuro-fuzzy rule-based systems for lung cancer detection and diagnosis, fuzzy logic systems for breast cancer risk prediction, etc.

A fuzzy logic technique for the prediction of the risk of breast cancer based on a set of judiciously chosen fuzzy rules utilizing patient age and automatically extracted tumor features (Sizilio, et al. 2012).

In this study a fuzzy expert system design for diagnosing, analyzing and learning purpose of the prostate cancer diseases a design of a fuzzy expert system for determination of the possibility of the diagnosis of the prostate cancer (Salah, et al. 2011).

4.7 Heart Diseases

Although there are various conditions that impact the heart, coronary artery disease (CAD) is the most prevalent and well-known. Heart attacks, heart failure, cardiac arrest, strokes, and organ damage can all result from heart disease. Congenital heart disease, coronary artery disease (CAD), arrhythmias, dilated cardiomyopathy, heart failure, myocardial infarction (MI), hypertrophic cardiomyopathy, and mitral regurgitation are among the several forms of heart illness.

Numerous factors, including gender, age, obesity, high blood pressure, high cholesterol, diabetes, family history, alcohol use, and smoking, increase the risk of heart disease. In addition, there are numerous other risks in this technologically advanced and contemporary environment,

Table 1. List of Research Papers in Medicine and Fuzzy Logic

Year	FL	FLM	Year	FL	FLM
1974	0	0	2003	141	11
1977	1	0	2004	182	25
1978	1	0	2005	195	11
1982	2	0	2006	278	13
1983	2	0	2007	257	18
1984	1	0	2008	292	17
1985	2	0	2009	313	17
1986	2	0	2010	339	24
1987	1	1	2011	334	15
1988	1	1	2012	346	17
1989	3	1	2013	336	13
1990	3	1	2014	360	24
1991	3	1	2015	347	36
1992	20	3	2016	350	37
1993	27	5	2017	333	35
1994	46	5	2018	349	30
1995	73	10	2019	396	24
1996	69	4	2020	386	36
1997	95	10	2021	430	37
1998	84	12	2022	531	34
1999	90	14	2023	356	26
2000	96	12	2024	570	49
2001	151	24	2025	589	50
2002	119	8			

doi: 10.13053/CyS-30-1-6335

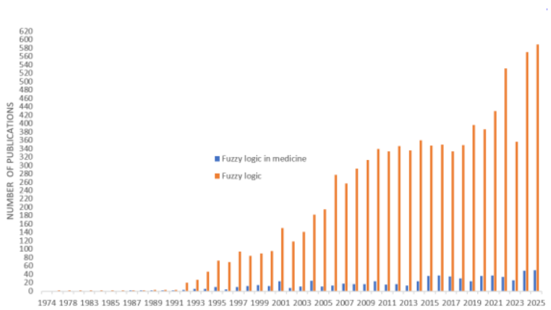

Fig. 3. Graph of annual publications using fuzzy logic and medicine

Table 2. List of Research Papers on Type-2 Fuzzy Logic

Year	T2FL	Year	T2FL
1997	1	2015	5
2001	1	2016	3
2004	1	2017	8
2006	1	2018	8
2008	5	2019	6
2009	2	2020	3
2010	3	2021	10
2011	7	2022	16
2012	6	2023	3
2013	4	2024	9
2014	12	2025	11

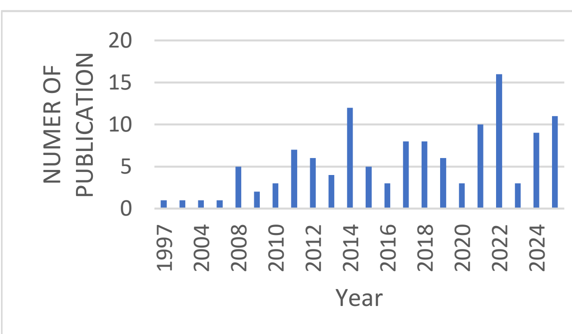

Fig. 4. Graph of annual publications using Type-2 fuzzy logic

including underemployment, industrialization, job overload, physical inactivity, melancholy, stress, and ever-increasing dietary and habit changes. With the aid of professionals and artificial intelligence, fuzzy logic is continuously being improved to identify cardiac patients globally.

Fuzzy rule-based system for the diagnosis of heart disease (Adeli and Neshat 2010), system that diagnoses congenital heart disease (CHD) using fuzzy logic and evaluates its functionality (Kahtan, et al. 2018).

4.8 Arthritis

Inflammation, discomfort, stiffness, and deformity are the main symptoms of a group of illnesses called arthritis, which can be persistent and even incapacitating.

It affects approximately three-quarters of patients with osteoarthritis and undiagnosed rheumatoid arthritis, which can increase the risk of the disease worsening. As a result, it is critical to identify the kind of arthritis and any associated musculoskeletal abnormalities as soon as feasible.

A system for the diagnosis of Arthritis using fuzzy logic controller (Baig, Gholamhosseini and Harrison 2012), early detection of arthritis using a diffuse system (Samridhi 2020).

4.9 Asthma

In order to obtain the best possible treatment outcomes and personal well-being, asthma, a complicated chronic respiratory disease, necessitates individualized monitoring and presents major management problems.

This study presents a fuzzy decision support system (FDSS) for personalized asthma monitoring, which leverages semantic reasoning techniques and SPARQL queries to improve decision-making accuracy and provide individualized assessments of asthma control (Chatterjee 2024).

5 Review of Fuzzy Logic in Medicine Using Type-1 and Type-2

This section provides an overview of recent studies that apply Type-1 and Type-2 FL in the medical domain. In previous works, the MEDLINE database was used to identify medical publications

ISSN 2007-9737

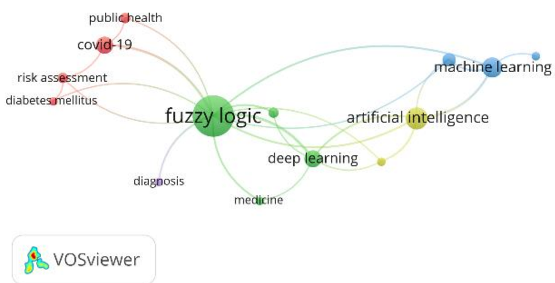

Fig. 5. Keyword maps

from 1990 to 2002 (Torres and Nieto 2006), The second article presents a study covering the period from 2000 to 2021 (Sharline and Sharline 2022)". In this article, we present the works published using fuzzy rules from the early beginnings of fuzzy logic in 1974 to October 20, 2025, as shown in Table 1. In 1977, the first publication on fuzzy logic was released, and in 1987, the article Fuzzy Logic Applied to Medicine was published.

Figure 3 shows graphs of articles published in the field of medicine. The perception that there are not a large number of publications on fuzzy logic in the field of medicine, compared to other areas, is due to several factors, including regulatory and trust challenges.

One of these factors is professional confidence ("Doctors and healthcare professionals trust their experience and clinical judgment, and although fuzzy logic can mimic approximate human reasoning, achieving widespread confidence in these systems for making critical healthcare decisions presents significant barriers").

The usefulness of fuzzy logic in medicine is endless. Physicians will have to accept that it is a useful tool that will be part of their daily activity. Patient care, as the essence of medicine, will continue to depend on interaction with the patient, and if repetitive routine activities are automated by fuzzy logic, then the physician-patient relationship will be significantly enhanced, providing quality time for the most relevant aspects of care (Lanzagorta-Ortega, Carrillo-Pérez and Carrillo-Esper 2022).

The field of medicine continues to evolve, and with advances in artificial intelligence and the need to manage the complexity of health data, the applications of fuzzy logic will increase. Table 2 shows the annual publications using type-2 FL, and Figure 4 shows the graphs of the annual publications.

In Figure 4, you can see that these keywords are divided into groups. Fuzzy logic is the crucial word. As seen in Figure 5, VOSviewer is based on reducing the distances between terms, meaning that the most similar keywords are put together in the same group.

6 Conclusions

After finishing the review, it is evident that type-1 or type-2 FL controllers have been used in several investigations. We can draw the conclusion that fuzzy logic plays a significant role in medicine when addressing practical issues.

As a result, using Type-1 and Type-2 FL is an excellent substitute for enhancing medical outcomes. Additionally, this research shows that the use of Type-1 and Type-2 fuzzy systems is growing in popularity, with authors employing fuzzy rules to enhance outcomes.

Using the data from PubMed, we have seen how the use of fuzzy rule-based systems is spreading throughout the medical sector as a result of researchers' positive outcomes. Additionally, hybrid approaches are also available in the literature to enhance outcomes.

Acknowledgments

The authors thank SECIHTI and the National Technological Institute of Mexico/Tijuana Technological Institute for their support during this research project. In addition, funding was also provided by the Academic Body: Intelligent Hybrid Systems.

References

1. **Zadeh, L. (1965).** Fuzzy sets, Information and Control, Vol. 8, No. 3, pp. 338–353.
2. **Zadeh, L. (1973).** Outline of a new approach to the analysis of complex systems and decision processes, IEEE Transactions on Systems, Man, and Cybernetics, No. 1, pp. 28–44.

3. **Braae, M. (1977).** Control Algorithms for Ill-defined Systems, Ph.D. Dissertation, The University of Manchester, United Kingdom.
4. **Zadeh, L. (1984).** Making computers think like people [fuzzy set theory], IEEE Spectrum, Vol. 21, No. 8, pp. 26–32.
5. **Korner, S. (1967).** Laws of Thought, Encyclopedia of Philosophy, Vol. 4.
6. **Hellmann, M. (2001).** Fuzzy Logic Introduction, Université de Rennes, Vol. 1, No. 1.
7. **Fernández, S., Velasco, J., López-Carmona, M. (2010).** Sistema basado en reglas difusas para el mapeo de ontologías, Congreso Español sobre Tecnologías y Lógica Fuzzy (ESTYLF 2010), Huelva, España.
8. **Gaxiola, F., Melin, P., Valdez, F., Castillo, O. (2014).** Interval Type-2 Fuzzy Weight Adjustment for Backpropagation Neural Networks with Application in Time Series Prediction, Information Sciences, Vol. 260, pp. 1–14.
9. **Gaxiola, F., Melin, P., Valdez, F., Castro, J., Castillo, O. (2016).** Optimization of Type-2 Fuzzy Weights in Backpropagation Learning for Neural Networks Using GAs and PSO, Applied Soft Computing, Vol. 38, pp. 860–871.
10. **Mendel, J. (2019).** Type-2 Fuzzy Sets as Well as Computing with Words, IEEE Computational Intelligence Magazine, Vol. 14, No. 1, pp. 82–95.
11. **Wu, D., Mendel, J. (2018).** Similarity Measures for Closed General Type-2 Fuzzy Sets: Overview, Comparisons, and a Geometric Approach, IEEE Transactions on Fuzzy Systems, Vol. 27, No. 3, pp. 515–526.
12. **Valdez, F., Castillo, O., Cortes-Antonio, P., Melin, P. (2020).** A Survey of Type-2 Fuzzy Logic Controller Design Using Nature Inspired Optimization, Journal of Intelligent & Fuzzy Systems, Vol. 39, No. 5, pp. 6169–6179.
13. **Castro, J., Castillo, O., Martinez, L. (2007).** Interval Type-2 Fuzzy Logic Toolbox, Engineering Letters, Vol. 15, No. 1, pp. 89–98.
14. **Navin, K., Krishnan, M., et al. (2024).** Fuzzy Rule Based Classifier Model for Evidence Based Clinical Decision Support Systems, Intelligent Systems with Applications, Vol. 22, pp. 200393.
15. **Gupta, K., Kumar, P., Upadhyaya, S., Poriye, M., Aggarwal, S. (2024).** Fuzzy Logic and Machine Learning Integration: Enhancing Healthcare Decision-Making, International Journal of Computer Information Systems and Industrial Management Applications, Vol. 16, No. 3, pp. 20–20.
16. **Berkhout, M., Smit, K., Versendaal, J. (2024).** Decision Discovery Using Clinical Decision Support System Decision Log Data for Supporting the Nurse Decision-Making Process, BMC Medical Informatics and Decision Making, Vol. 24, No. 1, pp. 100.
17. **Abdulbaqi, A., Al-Attar, B., Zaid Qudr, L., Penubadi, H., Sekhar, R., Shah, P., Parihar, S., Kallam, S., Tawfeq, J., et al. (2024).** Efforts of Neutrosophic Logic in Medical Image Processing and Analysis, International Journal of Neutrosophic Science (IJNS), Vol. 24, No. 4.
18. **Yadav, R., Singh, A., Yadav, S. (2024).** The Smart Fuzzy Based Image Recognition Model for Modern Healthcare, 2024 2nd International Conference on Disruptive Technologies (ICDT), pp. 250–254.
19. **Pour, J., Pourmina, M., Moghaddasi, M., Ghalamkari, B. (2024).** An Artificial Intelligent Network Model to Monitor the Condition of a Patient with a Breast Tumor Based on Fuzzy Logic, Health and Technology, Vol. 14, No. 1, pp. 119–139.
20. **Locatelli, M., Cerioli, R., Besozzi, D., Hommersom, A., Stella, F., et al. (2024).** Reinforcement Learning and Fuzzy Logic Modelling for Personalized Dynamic Treatment, CEUR Workshop Proceedings, Vol. 3880.
21. **Drnovšek, R., Milavec Kapun, M., Šteblaj, S., Rajkovič, U. (2025).** Multicriteria Risk Evaluation Model: Utilizing Fuzzy Logic for Improved Transparency and Quality of Risk Evaluation in Healthcare, Risk Management and Healthcare Policy, pp. 637–653.
22. **Mauseth, R., Hirsch, I., Bollyky, J., Kircher, R., Matheson, D., Sanda, S., Greenbaum, C. (2013).** Use of a “Fuzzy Logic” Controller in a Closed-Loop Artificial Pancreas, Diabetes Technology & Therapeutics, Vol. 15, No. 8, pp. 628–633.
23. **Ibbini, M. (2006).** A PI-Fuzzy Logic Controller for the Regulation of Blood Glucose Level in Diabetic Patients, Journal of Medical Engineering & Technology, Vol. 30, No. 2, pp. 83–92.
24. **Almutoory, M., Almutoory, A. (2025).** Real-Time Glucose Level Interpretation Using a Fuzzy Logic Framework for Diabetes Management, Sohar University Journal of Engineering and Information Technology Innovations, Vol. 1, No. 2.
25. **Elhoushy, M., Zalam, B., Sayed, A., Nabil, E. (2024).** Automated Blood Glucose Regulation for Nonlinear Model of Type-1 Diabetic Patient Under Uncertainties: GWOCS Type-2 Fuzzy Approach, Biomedical Engineering Letters, Vol. 14, No. 1, pp. 127–151.
26. **Nasar, N., Jaradat, M., Rhomdane, L. (2024).** Hybrid Intelligent Sliding Mode Controller for Blood Glucose Regulation, 2024 Advances in Science and Engineering Technology International Conferences (ASET), pp. 1–6.

27. **Al-Araji, A., Dagher, K., Abdullah, M. (2024).** Development of Intelligent Control Strategy for an Anesthesia System Based on Radial Basis Function Neural Network Like PID Controller, International Journal of Intelligent Engineering & Systems, Vol. 17, No. 3.

28. **Rahim, F., Deshpande, A., Hosseini, A. (2007).** Fuzzy Expert System for Fluid Management in General Anesthesia, Journal of Clinical and Diagnostic Research, Vol. 4, pp. 256–267.

29. **Baig, M., Gholamhosseini, H., Harrison, M. (2012).** Fuzzy Logic Based Smart Anaesthesia Monitoring System in the Operation Theatre, WSEAS Transactions on Circuits and Systems, Vol. 11, No. 1, pp. 21–32.

30. **Wei, Z.-X., Doctor, F., Liu, Y.-X., Fan, S.-Z., Shieh, J.-S. (2020).** An Optimized Type-2 Self-Organizing Fuzzy Logic Controller Applied in Anesthesia for Propofol Dosing to Regulate BIS, IEEE Transactions on Fuzzy Systems, Vol. 28, No. 6, pp. 1062–1072.

31. **El-Nagar, A., El-Bardini, M. (2014).** Interval Type-2 Fuzzy Neural Network Controller for a Multivariable Anesthesia System Based on a Hardware-in-the-Loop Simulation, Artificial Intelligence in Medicine, Vol. 61, No. 1, pp. 1–10.

32. **Niswati, Z., Mustika, F., Paramita, A. (2018).** Fuzzy Logic Implementation for Diagnosis of Diabetes Mellitus Disease at Puskesmas in East Jakarta, Journal of Physics: Conference Series, Vol. 1114, No. 1, pp. 012107.

33. **Ali, M., Sadi, M., Goni, M. (2024).** Diagnosis of Heart Diseases: A Fuzzy-Logic-Based Approach, PLOS ONE, Vol. 19, No. 2, pp. e0293112.

34. **Cordero-Martínez, R., Sánchez, D., Melin, P. (2024).** Adjustment of Convolutional and Hidden Layers Using Type-1 Fuzzy Logic Applied to Diabetic Retinopathy Classification, Computación y Sistemas, Vol. 28, No. 2, pp. 877–888.

35. **Atlas, E., Nimri, R., Miller, S., Grunberg, E., Phillip, M. (2010).** MD-Logic Artificial Pancreas System: A Pilot Study in Adults with Type 1 Diabetes, Diabetes Care, Vol. 33, No. 5, pp. 1072–1076.

36. **Tsai, D.-Y., Lee, Y., Sekiya, M., Ohkubo, M. (2004).** Medical Image Classification Using Genetic-Algorithm Based Fuzzy-Logic Approach, Journal of Electronic Imaging, Vol. 13, No. 4, pp. 780–788.

37. **Ahmadi, M., Dashti Ahangar, F., Astaraki, N., Abbasi, M., Babaei, B. (2021).** FWNNet: Presentation of a New Classifier of Brain Tumor Diagnosis Based on Fuzzy Logic and the Wavelet-Based Neural Network Using Machine-Learning Methods, Computational Intelligence and Neuroscience, Vol. 2021, No. 1, pp. 8542637.

38 **Banerjee, A., Bhattacharya, R., Bhateja, V., Singh, P., Sarkar, R., et al. (2022).** COFE-Net: An Ensemble Strategy for Computer-Aided Detection for COVID-19, Measurement, Vol. 187, pp. 110289.

39 **Alsheikhy, A., Said, Y., Shawly, T., Alzahrani, A., Lahza, H. (2022).** Biomedical Diagnosis of Breast Cancer Using Deep Learning and Multiple Classifiers, Diagnostics, Vol. 12, No. 11, pp. 2863.

40. **Hernández-Delgado, J., Cruz-Aceves, I., Cordova-Fraga, T., Sosa-Aquino, M., Guzman Cabrera, R. (2019).** Processing of MRI Images Weighted in TOF for Blood Vessels Analysis: 3-D Reconstruction, Computación y Sistemas, Vol. 23, No. 1, pp. 109–114.

41. **Singh, S., Abolghasemi, V., Anisi, M. (2023).** Fuzzy Logic with Deep Learning for Detection of Skin Cancer, Applied Sciences, Vol. 13, No. 15, pp. 8927.

42. **Khan, A., Narejo, G. (2019).** Analysis of Abdominal Computed Tomography Images for Automatic Liver Cancer Diagnosis Using Image Processing Algorithm, Current Medical Imaging Reviews, Vol. 15, No. 10, pp. 972–982.

43. **Narayanan, K., Krishnan, R., Son, L., Tung, N., Julie, E., Robinson, Y., Kumar, R., Gerogiannis, V. (2022).** Fuzzy Guided Autonomous Nursing Robot Through Wireless Beacon Network, Multimedia Tools and Applications, Vol. 81, No. 3, pp. 3297–3325.

44. **Kosa, G., Morozov, O., Lehmann, A., Pargger, H., Marsch, S., Hunziker, P. (2023).** Robots and Intelligent Medical Devices in the Intensive Care Unit: Vision, State of the Art, and Economic Analysis, IEEE Transactions on Medical Robotics and Bionics, Vol. 5, No. 1, pp. 2–17.

45. **Ragu, P., Swathi Sri, R. (2022).** Controlling of Surgical Robotics Platform for Endoscopic Using Fuzzy Logic Controller, International Research Journal of Modernization in Engineering Technology and Science, Vol. 4, No. 6, pp. 3478–3484.

46. **Mago, V., Mago, A., Sharma, P., Mago, J. (2011).** Fuzzy Logic Based Expert System for the Treatment of Mobile Tooth, Software Tools and Algorithms for Biological Systems, Springer, pp. 607–614.

47. **Hashem, M., Mohammed, M., Youssef, A. (2020).** Improving the Efficiency of Dental Implantation Process Using Guided Local Search Models and Continuous Time Neural Networks with Robotic Assistance, IEEE Access, Vol. 8, pp. 202755–202764.

48. **Bouteraa, Y., Abdallah, I., ElMogy, A., Ibrahim, A., Tariq, U., Ahmad, T. (2020).** A Fuzzy Logic Architecture for Rehabilitation Robotic Systems, International Journal of Computers Communications & Control, Vol. 15, No. 4.

49. **Sang, H., Yang, C., Liu, F., Yun, J., Jin, G. (2016).** A Fuzzy Neural Network Sliding Mode Controller for Vibration Suppression in Robotically Assisted Minimally Invasive Surgery, The International Journal of Medical Robotics and Computer Assisted Surgery, Vol. 12, No. 4, pp. 670–679.
50. **Huang, J., Zhu, D., Tang, Y. (2017).** Health Diagnosis Robot Based on Healthcare Big Data and Fuzzy Matching, Journal of Intelligent & Fuzzy Systems, Vol. 33, No. 5, pp. 2961–2970.
51. **Sizilio, G., Leite, C., Guerreiro, A., Neto, A. (2012).** Fuzzy Method for Pre-Diagnosis of Breast Cancer from the Fine Needle Aspirate Analysis, Biomedical Engineering Online, Vol. 11, No. 1, pp. 83.
52. **Salah, B., Alshraideh, M., Beidas, R., Hayajneh, F. (2011).** Skin Cancer Recognition by Using a Neuro-Fuzzy System, Cancer Informatics, Vol. 10, pp. CIN–S5950.
53. **Adeli, A., Neshat, M. (2010).** A Fuzzy Expert System for Heart Disease Diagnosis, Proceedings of International Multi Conference of Engineers and Computer Scientists, Hong Kong, Vol. 1.
54. **Kahtan, H., Zamli, K., Fatthi, W., Abdullah, A., Abdulleteef, M., Kamarulzaman, N. (2018).** Heart Disease Diagnosis System Using Fuzzy Logic, Proceedings of the 2018 7th International Conference on Software and Computer Applications, pp. 297–301.
55. **Samridhi, D. (2020).** Early Detection of Arthritis Using Hierarchical Fuzzy Expert System, International Journal for Research in Applied Science & Engineering Technology (IJRASET), Vol. 8, No. 2, pp. 326–333.
56. **Chatterjee, A. (2024).** A Fuzzy Decision Support System with Semantic Knowledge Graph for Personalized Asthma Monitoring: A Conceptual Modeling, Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, Vol. 2, pp. 143–150.
57. **Torres, A., Nieto, J. (2006).** Fuzzy Logic in Medicine and Bioinformatics, BioMed Research International, Vol. 2006, No. 1, pp. 091908.
58. **Sharline, U., Sharline, J. (2022).** Impact of Fuzzy Logic and Its Applications in Medicine: A Review, International Journal of Statistics and Applied Mathematics, Vol. 7, pp. 20–27.
59. **Lanzagorta-Ortega, D., Carrillo-Pérez, D., Carrillo-Esper, R. (2022).** Inteligencia artificial en medicina: presente y futuro, Gaceta Médica de México, Vol. 158, pp. 17–21.

Article received on 31/10/2025; accepted on 15/12/2025.
**Corresponding author is Prometeo Cortés-Antonio.*