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Challenges and Future Trends in Fuzzy Logic: A Comprehensive Review

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Abstract. The real world is a fuzzy world, so to deal with fuzzy reality, what is needed is fuzzy logic. (Lotfi A. Zadeh). Fuzzy logic, since its origin, has proven its utility to handle uncertainty and imprecise information across diverse domains. This review paper aims to provide an in-depth overview of current challenges and future directions within Fuzzy logic. The research methodology was a systematic review of 30 newly published research studies obtained from high-reputation journals and online repositories. A systematic literature review table was constructed to summarise key contributions and identify research gaps in the literature. Key findings suggest that fuzzy logic remains highly active in hybrid systems—particularly with comparisons against neural networks and machine learning—and still struggles with scalability, real-time responsiveness, interpretability, as well as standardization challenges. We explore the limitations of traditional fuzzy systems, including rule-based design complexities and computational complexities, and highlight the advancements in hybrid approaches. We discuss the emerging trends in fuzzy logic, including type-2 fuzzy systems, the integration with machine learning, artificial intelligence and deep learning, aiming to enhance robustness in AI models. Moreover, we also discuss the applications of fuzzy logic in control systems, decision making, image processing and emerging technologies like IoT and robotics and discuss the problems that affect its potential. This review identifies important future research directions, which include the development of efficient deep fuzzy architectures and the continued refinement of theoretical foundations. By synthesising the current literature, this review provides a broad overview for the researchers and practitioners facing the challenges and future directions by highlighting the continuous evolution and future potential of fuzzy logic.

Keywords: Fuzzy logic, type-2 fuzzy systems, Machine learning, Deep learning, Image processing, Intelligent Systems, Computational Reasoning, Decision Support Systems.

AMS Mathematics Subject Classification (2010): 94D05

1. Introduction to fuzzy logic

1.1. Core principles and historical context

Unlike classical logic, fuzzy logic directly addresses uncertainty and imprecision; thus, it is a useful instrument in many different fields [1]. Its application in many fields, including pattern recognition, classification, and control systems [2], results from its capacity to manage vague and uncertain linguistic information. Lotfi Zadeh first presented fuzzy logic as a mathematical framework to handle the idea of vagueness, which is inherent in much of human thinking and decision-making [3, 4], back in 1965. This divergence from conventional binary logic, which requires that a statement be either true or false, lets fuzzy logic give degrees of truth to statements, so more in line with human understanding and interpretation of knowledge. The adoption of fuzzy logic represented a major paradigm change in handling real-world issues defined by insufficient or inaccurate data. Since then, this creative idea has been developed and used in many different disciplines proving its adaptability and strength in managing challenging systems.

Fuzzy logic's fundamental idea is its capacity to use fuzzy sets to represent and control imprecise knowledge. Whereas Fuzzy sets allow elements to have partial membership, quantified by a membership function that assigns a value between 0 and 1, Classical sets let elements either belong or do not belong to a set. This membership function shows the element's degree of fuzzy set membership. For example, take the fuzzy set "tall." In classical logic, a person would either be deemed tall or not depending on a particular height threshold. In fuzzy logic, a person's membership in the "tall" set would progressively rise with increasing height, so allowing a more complex depiction of the idea. fuzzy logic is especially suited for modelling real-world events that are often vague and subjective since this ability to manage slow changes and partial memberships helps one to handle them.

The historical background of fuzzy logic is firmly anchored in the necessity to solve the constraints of classical logic in handling pragmatic issues. Applied to circumstances involving uncertainty, ambiguity, or linguistic imprecision, traditional logic systems—with their binary true-or-false character—often prove inadequate. Lotfi Zadeh saw this discrepancy and suggested fuzzy logic to close the distance between the imprecision of human language and thought and the accuracy of mathematics. Some areas of the scientific community first greeted fuzzy logic with mistrust since they saw it as a break from accepted mathematical rigour. But fuzzy logic's pragmatic value in many different contexts—from decision-making to control systems—gradually helped it to be widely adopted. Attesting to its continuing relevance and impact, fuzzy logic has developed from a theoretical idea to a useful tool with many applications across several sectors over the decades.

1.2. Scope of review

This review attempts to fully address, in the field of decision-making, the theoretical foundations and useful applications of fuzzy logic [2]. It will investigate the basic ideas of fuzzy logic—that is, fuzzy sets, membership functions, and fuzzy inference systems—and look at how these ideas are used in several approaches of decision-making. Furthermore, covered in the review will be particular uses of fuzzy logic in fields including group decision-making, prediction, evaluation, and decision support systems. This review aims to give a complete knowledge of fuzzy logic's function in decision-making procedures by giving a broad summary of its theoretical and pragmatic features.

By means of different angles, the review will also highlight difficulties and future trends, so providing insights on the present situation of the field and possible directions of future research [2]. It will cover the shortcomings of fuzzy logic, including the computational complexity of some fuzzy systems and the subjectivity in defining membership functions. Moreover, the review will investigate new and developing applications of fuzzy logic in diverse fields as well as developing trends in fuzzy logic research including the integration of fuzzy logic with other artificial intelligence techniques including neural networks and machine learning. This paper attempts to give a fair and forward-looking view of the field of fuzzy logic by analysing both the difficulties and future trends.

Emphasising the synergy between fuzzy logic and artificial intelligence (AI), this review will investigate newly developed methods supported by these two domains [6]. Combining fuzzy logic with artificial intelligence has produced hybrid intelligent systems with the best features of both methods. While artificial intelligence methods including neural networks and machine learning give potent tools for learning and adaptation, fuzzy logic offers a framework for representing and reasoning with uncertainty. From control systems to pattern recognition to decision-making, the combination of fuzzy logic and artificial intelligence has produced creative answers to difficult challenges in many fields. Some of these new approaches and applications will be discussed in this review, highlighting the possibilities of fuzzy logic and artificial intelligence to change many spheres of our life.

2. Literature review in the field

We have investigated 30 research publications covering several uses and developments in the field of fuzzy logic in this literature review study. The review study tracked the procedure shown in Figure 1. By means of a thorough investigation, we gained important understanding, especially with regard to the constraints and difficulties that define present research. These results draw attention to important research voids covered in later parts. The table below provides the synopsis of this extensive study.

Table 1: Table of relevant information obtained from papers

Ref. No	**Major Outcome of Study**	**Major Challenges/Limitations as Research Gaps**
[1]	Fuzzy logic enhances decision support systems in complex environments.	Integration with traditional systems remains limited.
[2]	Provided comprehensive methods and future trends in fuzzy decision support.	Lack of adaptive real-time implementation frameworks.
[3]	Highlighted medical diagnosis improvements via fuzzy logic.	Inconsistency in clinical data modeling.
[4]	Described fuzzy set theory’s AI integration in decision-making.	Ambiguity in rule-based systems scalability.

[5]	Fuzzy logic's application in hardware and computer technology is increasing.	Hardware compatibility and standardization issues.
[6]	Introduced emerging AI techniques with fuzzy logic.	Lack of benchmark datasets for performance testing.
[7]	Applied fuzzy controllers in PV systems for efficient power conversion.	Real-time tuning under environmental variations is complex.
[8]	Compared membership functions and defuzzification methods for air quality.	Standard criteria for method selection is lacking.
[9]	Demonstrated fuzzy logic's role in video surveillance analytics.	High computational cost for real-time processing.
[10]	Reviewed fuzzy logic applications in nonlinear control systems.	Generalization for unknown system models is limited.
[11]	Emphasized integration of fuzzy systems in decision support architecture.	Handling high-dimensional data is still challenging.
[12]	Combined fuzzy logic with MCDM techniques across sectors.	High complexity in multi-parameter decision models.
[13]	Proposed intelligent fuzzy controllers for industrial automation.	Difficulty in handling real-time fault tolerance.
[14]	Integrated fuzzy logic with AI in power grid systems.	Lack of dynamic learning in complex networks.
[15]	Used fuzzy-based prediction systems for learning behaviour modelling.	Subjectivity in cognitive style classification.
[16]	Optimized mutual fund selections using fuzzy Sharpe ratios.	Fuzzy outputs need clearer interpretation for investors.
[17]	Discussed fuzzy logic in robotics for intelligent decisions.	Limited adaptability in uncertain robotic environments.
[18]	Reviewed fuzzy logic in traffic signal control systems.	Sensor integration issues and real-world noise impact.
[19]	AI-fuzzy logic applied to offshore wind energy optimization.	Hybrid model calibration is time-consuming.
[20]	Assessed AI's role in power system protection and control.	Interoperability of AI-fuzzy modules in legacy grids.
[21]	Used bibliometric techniques to trace fuzzy logic in finance.	Sparse application in dynamic real-time stock prediction.
[22]	Fuzzy logic applied to candlestick pattern recognition.	Overfitting risk in volatile markets.
[23]	Improved smart home automation using fuzzy logic.	Security and protocol compatibility challenges.
[24]	Designed fuzzy-IoT systems for smart drug storage.	Lack of edge-device optimization.

[25]	Demonstrated fuzzy logic in traffic management automation.	Needs integration with cloud-based analytics.
[26]	fuzzy rule-based task offloading approach for edge computing to optimize task allocation between edge, local, and cloud servers	Performance prediction is further complicated by the unpredictability of hardware, network conditions, and user requirements.
[27]	a fuzzy logic-based system to evaluate digital copyright value more comprehensively and intelligently, addressing challenges in traditional valuation methods.	fuzzy logic model has been tested on a limited dataset
[28]	fuzzy logic enhances deep learning models by improving representation accuracy and handling data noise.	Deep learning models are vulnerable to noisy data, and while fuzzy logic can help mitigate this issue, further studies are required to refine hybrid approaches for better robustness.
[29]	refining fuzzy logic models and integrating them with AI-driven optimization techniques could further enhance their effectiveness in RAC applications.	Limited Comparative Analysis
[30]	Integrating fuzzy logic into software development processes can lead to better decision-making and improved software reliability.	fuzzy logic has not been widely integrated to address the ambiguous nature of quality parameters.

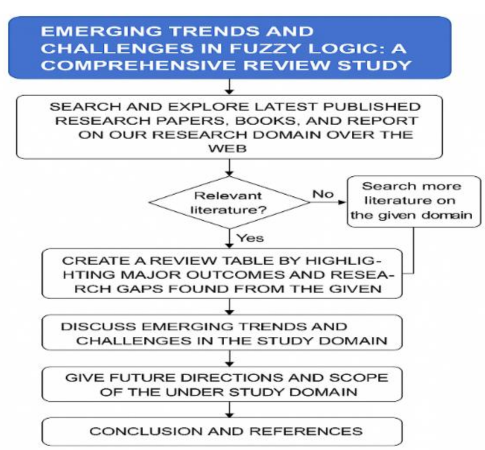

Figure 1: Review Study Process

Applying fuzzy logic across many fields—including decision support, medical diagnosis, automation, energy systems, and financial analytics—shows notable advancement in the literature review. Still, a number of restrictions exist, including poor real-time adaptability, absent standardised datasets and benchmarks, and challenges merging fuzzy logic with artificial intelligence in dynamic surroundings. Moreover, main obstacles are system scalability, interoperability with legacy technologies, and high computational demand. Development of adaptive fuzzy models, lightweight architectures for IoT deployment, and frameworks for integrating fuzzy logic with machine learning for improved intelligent decision-making should be the main priorities of next studies. These initiatives will improve the theoretical strength and useful implementation of fuzzy systems in important fields.

3. Theoretical challenges in fuzzy logic

3.1. Membership function design

In fuzzy logic systems, designing the limits for membership functions sometimes calls for hand tuning, which can be time-consuming and demanding [7]. Because they define the degree to which an element belongs to a fuzzy set, membership functions are fundamental parts of fuzzy logic systems. The behaviour and performance of the fuzzy system depend much on the form and limits of these functions. Still, figuring out the best membership functions for a given application is sometimes difficult. Usually involving a trial-and-error process, the designer personally changes the membership function parameters depending on their experience and sense of intuition. Particularly for intricate systems with many input variables and fuzzy sets, this manual tuning process can be especially time-consuming and difficult.

Although several mathematical formulas have been suggested to enhance membership functions, their practical application is sometimes restricted to classical functions, so limiting the influence of other ideas [8]. There are several kinds of membership functions: triangular, trapezoidal, Gaussian, and sigmoid ones. Every type has benefits and drawbacks; the particular application and the nature of the data under modelling will determine the membership function to be chosen. Although many mathematical formulations have been developed to produce more complex and flexible membership functions, most useful applications still depend on the more conventional and simpler functions. This is sometimes the result of the simplicity of implementation and interpretation of these classical functions as well as the absence of explicit rules for choosing the most suitable function for a given problem.

The performance of fuzzy systems is much influenced by the choice of suitable membership functions, which emphasises the need of careful design [8]. The accuracy, robustness, and interpretability of the fuzzy system can be changed by the membership function selection. For instance, a system may be too sensitive to minute variations in the input variables if the membership functions are too narrow. On the other hand, a too broad membership function could prevent the system from differentiating between various input values. Consequently, it is imperative to give great thought to the features of the problem under discussion and choose membership functions fit for the work. To find the ideal membership functions for a given fuzzy system, one often combines theoretical knowledge, practical experience, and experimentation.

3.2. Rule base development

Since the rules must precisely capture the interactions between input and output variables [7], developing effective fuzzy rules is a difficult process requiring major domain expertise. Since they define how the system maps input values to output values, fuzzy rules form the core of a fuzzy inference system. Usually expressed as "IF-THEN," these guidelines have the "IF" component indicate a condition dependent on the input variables and the "THEN" component indicate the matching output value. Building these rules calls both a thorough awareness of the problem under discussion and the relationships between the input and output variables. This usually entails speaking with subject-matter experts with a great deal of field experience. The performance of the fuzzy system is directly related to the quality of the fuzzy rules, thus rule base development is a very important phase of design.

To guarantee the accuracy and dependability of the fuzzy system [7], one has to be able to verify the completeness, redundancy, and consistency of fuzzy rules. Completeness in the context of rules is their capacity to encompass every conceivable input situation. Redundancy in the context of rules is the existence of several ones producing the same output for a given input. Consistency is the absence of contradicting policies producing different outputs for the same input. Verifying these characteristics guarantees that the fuzzy system generates accurate results and operates as expected. Several methods have been developed to examine and confirm the completeness, redundancy, and consistency of fuzzy rule bases, so strengthening the dependability and credibility of fuzzy systems.

A fuzzy system's exponential increase in rules with increasing input variables presents a major difficulty for complicated problems [7]. Especially for systems with many input variables, this phenomenon—known as the "curse of dimensionality—can make rule-based development an intimidating choreography. Design, implementation, and maintenance of a fuzzy system get more challenging as the number of rules rises since their complexity grows as well. Several approaches have been developed to handle this difficulty, including evolutionary algorithms, hierarchical fuzzy systems, and rule-reducing techniques. These methods seek to minimise the rules while maintaining the accuracy and performance of the fuzzy system, so enabling the management and scalability of the system for challenging applications.

3.3. Computational complexity

Particularly for difficult problems involving many rules and input variables, fuzzy logic systems can be computationally taxing [9]. The computation complexity stems from the need to apply fuzzy rules, evaluate membership functions for each input variable, and subsequently defuzzify the output. Particularly for real-time applications where quick response times are demanded, these activities can be time-consuming. For embedded systems with limited CPU and memory, the computational load can also be rather heavy. Consequently, effective hardware implementations and algorithms are required to lower the computational complexity of fuzzy logic systems and enable their fit for a greater spectrum of uses.

Designing fuzzy logic systems presents a great difficulty in juggling accuracy and computational efficiency since expanding the number of rules and membership functions can enhance accuracy but also raise computational complexity [9]. Designing a fuzzy system for a particular use requires careful evaluation of this trade-off between accuracy and efficiency. Sometimes the necessary computational performance calls for some accuracy sacrificed in order to Rule reduction approaches, simplified membership functions, and parallel processing are among the several ways one can handle this trade-off. The objective is to strike a balance offering the best possible performance within the given computational limitations.

To enable the use of fuzzy logic in real-time applications, where timely responses are vital [9], effective algorithms and hardware implementations are indispensable. Real-time applications including autonomous cars and industrial control systems call for fuzzy logic systems to rapidly and consistently process data and make decisions. This calls for hardware implementations that can run effective algorithms in parallel as well as for minimising computational load by means of such algorithms. FPGAs and GPUs among other hardware platforms have been used to speed the execution of fuzzy logic systems, so enabling their use in demanding real-time applications. Research on the development of effective algorithms and hardware implementations is continuous since it will help to make fuzzy logic systems more accessible and useful for a greater spectrum of applications.

4. Integration with other AI techniques

4.1. Fuzzy logic and neural networks

Combining fuzzy logic with neural networks can produce hybrid intelligent systems that use the strengths of both approaches, so producing increased performance and adaptability [13, 14]. While neural networks give potent tools for learning and adaptation, fuzzy logic offers a framework for expressing and reasoning with uncertainty. Combining these two methods allows hybrid intelligent systems to solve challenging problems using either method by themselves. Comparatively to conventional approaches, these systems offer enhanced performance and resilience since they can be applied in several uses including control systems, pattern recognition, and decision-making.

By means of learning, neural networks can maximise fuzzy logic systems so enabling the system to adapt to changing circumstances and hence enhance its performance over time [15]. Furthermore used to find the most pertinent input variables for a given problem and to learn the optimal parameters of fuzzy membership functions and rules are neural networks. While increasing their accuracy and resilience, this can greatly cut the time and effort needed to design and tune fuzzy logic systems. Using neural networks to maximise fuzzy logic systems helps one to design intelligent systems capable of learning from data and adjusting to changing surroundings.

Fuzzy logic improves the explainability of neural network models, so increasing their transparency and understandable nature for human users [6]. Many times attacked for being "black boxes," neural networks can be challenging to understand how they get at their decisions. A more transparent and understandable depiction of the knowledge acquired by the neural network can be given by fuzzy logic. Extraction of fuzzy rules from the trained neural network helps one to understand the connections between the input and output variables, so strengthening the model's dependability. Applications like financial analysis and medical diagnosis, where openness and responsibility are absolutely crucial, depend on this especially.

4.2. Fuzzy logic and machine learning

Combining fuzzy logic models with machine learning improves mutual fund evaluations by offering a more complete and nuanced view of fund performance [16]. While fuzzy logic can manage the uncertainty and imprecision inherent in the market, machine learning techniques can be used to find trends and relationships in financial data. Combining these two methods helps one produce more accurate and dependable models for assessing mutual fund performance, so guiding investors towards more wise decisions. Improved investment results and a better knowledge of the hazards and possibilities in the market can follow from this integration.

Whereas fuzzy logic can be used to manage and maximise the maintenance process, machine learning techniques can forecast equipment failures in industrial automation [13]. Using data analysis and machine learning to find possible equipment failures before they happen helps to enable proactive maintenance and lower downtime by means of predictive maintenance. Control strategies for allocating resources, planning maintenance activities, and maximising the general maintenance process can be created with fuzzy logic. Intelligent maintenance systems able to increase the dependability and efficiency of industrial automation processes can be produced by combining fuzzy logic with machine learning.

Large-sized artificial intelligence models can benefit from fuzzy logic as a complementing tool to help to manage domain uncertainty and create easily flexible and explainable data-based models [9]. Large artificial intelligence models can be challenging to grasp and interpret and sometimes call for enormous volumes of data and computational tools. These models can be simplified, their computational complexity lowered, and their interpretability raised by means of fuzzy logic's application. Including fuzzy logic into artificial intelligence systems helps to produce more transparent, strong, and efficient models fit for a greater spectrum of use. Improved performance and a better knowledge of the fundamental processes under modelling can result from this integration.

5. Emerging trends in fuzzy logic research

5.1. Type-2 fuzzy logic

By managing the uncertainty related with words and their meanings, type-2 fuzzy sets can provide an efficient paradigm supporting accurate understanding of natural language [6]. Natural language is by nature vague; words have several connotations and interpretations. Type-2 fuzzy sets enable the membership functions themselves to be fuzzy, so reflecting this uncertainty. This enables a more complex and strong representation of natural language, so enhancing performance in uses including machine translation and natural language processing. Type-2 fuzzy sets allow one to design systems able to grasp and react to the complexity of human language.

Unlike conventional type-1 fuzzy logic, type-2 fuzzy logic manages higher degrees of uncertainty and imprecision, hence it is appropriate for uses where the data is quite uncertain or unreliable [6]. The membership functions of type-1 fuzzy logic are crisp; hence, every element has exactly a degree of membership in a fuzzy set. The membership functions of type-2 fuzzy logic are fuzzy; thus, the degree of membership is likewise uncertain. This enables type-2 fuzzy logic to manage more degrees of uncertainty and imprecision, hence fitting for uses including decision-making with limited information and control systems in noisy surroundings. Type-2 fuzzy logic allows one to design systems more dependable and stronger in the face of ambiguity.

By offering a more transparent and understandable depiction of the reasoning process, type-2 fuzzy logic is applied in explainable artificial intelligence [6]. Research on explainable artificial intelligence—that is, making AI systems more understandable and transparent for human consumers—is expanding. AI systems that are more explainable by clearly and intuitively presenting the reasoning process can be produced using type-2 fuzzy logic. Human users can readily grasp the fuzzy rules and membership functions, which helps them to know how the system gets at its decisions. Applications like financial analysis and medical diagnosis, where openness and responsibility are absolutely crucial, depend on this especially.

5.2. Fuzzy deep learning

Combining the strengths of both methods will help fuzzy logic to be included with deep learning models for better performance [13], [14]. Powerful tools for learning patterns from data, deep learning models sometimes find it difficult to manage uncertainty and ambiguity. Fuzzy logic offers a structure for expressing and reasoning with this uncertainty, so enabling deep learning models to function more precisely in challenging and uncertain settings. Systems that reach better degrees of accuracy, resilience, and adaptability can be produced by combining fuzzy logic with deep learning. In image recognition, natural language processing, and control systems among other fields, this hybrid approach has shown promise.

Combining the strengths of both approaches, fuzzy deep learning produces more strong, efficient, interpretable models [13, 14]. While deep learning offers strong tools for learning intricate patterns from data, fuzzy logic offers a structure for expressing and reasoning with uncertainty. Combining these two methods helps one to produce models with interpretability and accuracy. Applications like financial analysis and medical diagnosis where openness and responsibility are crucial depend on this especially. By revealing the reasoning process, fuzzy deep learning models help users to grasp how the system gets at its decisions.

By means of a more transparent and understandable representation of the learnt knowledge, fuzzy logic improves the interpretability of deep learning models [13, 14]. Many times attacked for being "black boxes," deep learning models can be challenging to grasp how they come at their conclusions. From the trained deep learning model, fuzzy rules can be extracted using fuzzy logic, so offering a more open and interpretable form of the learnt knowledge. This helps consumers to grasp the links between the input and output variables, so strengthening the model's dependability. Using fuzzy logic to improve the interpretability of deep learning models helps one to design artificial intelligence systems that are both strong and comprehensible.

6. Challenges in implementing fuzzy logic

6.1. Scalability

The computational complexity of evaluating fuzzy rules and membership functions [19] makes scaling fuzzy logic systems difficult for handling big and complicated problems. Applications of fuzzy logic to high-dimensional problems become challenging as computational complexity rises with the number of input variables and rules [9]. Real-time applications must address scalability concerns and enable timely responses by means of effective algorithms and hardware implementations [9].

Implementing fuzzy logic presents a major difficulty in scalability, especially for large and complicated problems, including many input variables and rules. Applying fuzzy logic to high-dimensional problems becomes challenging as the computational complexity of assessing fuzzy rules and membership functions rises with increasing number of inputs and rules. Effective algorithms and hardware implementations are required to lower the computational load and enable real-time applications in order to handle these scalability difficulties.

6.2. Interpretability

Maintaining the interpretability of fuzzy logic systems as complexity rises is a difficulty since the rule base can get difficult to grasp and change [6]. Designing fuzzy logic systems depends on careful balancing accuracy and interpretability since increasing system complexity can both improve accuracy and lower interpretability [6]. By means of a framework for understanding and interpreting the decisions taken by the models, fuzzy logic improves the explainability of artificial intelligence models [6].

Implementing fuzzy logic also depends much on interpretability. Although fuzzy logic is usually thought to be more interpretable than other artificial intelligence methods, such neural networks, keeping fuzzy logic systems interpretable as complexity rises can prove difficult. Maintaining the transparency and explainability of the system can prove difficult as the rule base gets bigger and more complicated. This makes modification difficult as well. Designing fuzzy logic systems requires careful balancing of accuracy and interpretability since increasing system complexity can improve accuracy but also lower interpretability. By offering a structure for comprehending and analysing the decisions taken by artificial intelligence models, fuzzy logic can improve their explainability.

6.3. Data requirements

For training and validation to guarantee correct and dependable performance, fuzzy logic systems need enough relevant data [9]. Implementing fuzzy logic depends critically on handling incomplete or imprecise data since real-world data is often noisy and uncertain [25]. Fuzzy logic addresses uncertainty and vagueness in data, so enabling a means of reasoning with imprecise information and guiding decisions in the face of incomplete or ambiguous data [3].

Implementing fuzzy logic takes great thought on data needs. For training and validation to guarantee correct and dependable performance, fuzzy logic systems need enough pertinent data. Implementing fuzzy logic depends critically on handling incomplete or imprecise data since real-world data is often noisy and uncertain. Fuzzy logic addresses uncertainty and vagueness in data, so offering a way to reason with imprecise knowledge and make decisions in the face of incomplete or dubious data.

7. Future directions

7.1. Hybrid intelligent systems

Future studies will concentrate on combining fuzzy logic with other artificial intelligence methods including neural networks, machine learning, and evolutionary algorithms, to generate hybrid intelligent systems using the advantages of each approach [12, 13]. By combining the capacity of fuzzy logic to manage uncertainty with the capacity of other artificial intelligence techniques to learn from data and optimise performance, hybrid systems enhance the resilience and adaptability of complex systems [10]. By means of a framework for understanding and interpreting the decisions rendered by the models, fuzzy logic improves the explainability and interpretability of artificial intelligence models [6].

Future fuzzy logic research could find great direction in hybrid intelligent systems. Systems that combine fuzzy logic with other artificial intelligence methods—such as neural networks, machine learning, and evolutionary algorithms—are more robust, flexible, and interpretable than systems depending on any one technique. By combining the ability of fuzzy logic to manage uncertainty with the ability of other artificial intelligence techniques to learn from data and maximise performance, hybrid systems enhance the robustness and adaptability of complex systems. By means of a framework for comprehending and interpreting the decisions taken by the models, fuzzy logic improves the explainability and interpretability of artificial intelligence models.

7.2. Adaptive fuzzy systems

Dynamic and uncertain environments where conditions can vary fast and unpredictably call for adaptive fuzzy logic systems [10]. Adaptive systems can preserve ideal performance in the face of uncertainty by modifying their parameters and rules depending on changing conditions [10]. By means of a means to learn from experience and adapt to changing conditions in real-time, fuzzy logic controllers with adaptive capabilities enhance performance [13].

8. Conclusion

Fuzzy logic remains a valuable tool for addressing uncertainty and imprecision in various domains, offering a flexible and intuitive approach to modeling complex systems [2]. Future research will focus on addressing current challenges, such as scalability and interpretability, and exploring new applications of fuzzy logic in emerging areas, such as the Internet of Things and big data analytics [10]. The combination of fuzzy logic and other AI techniques offers extensive research prospects, promising to lead to new and powerful tools for addressing complex problems in a wide range of domains [2]. The ongoing exploration and refinement of fuzzy logic methodologies will undoubtedly pave the way for more intelligent, adaptive, and robust systems in the years to come.

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