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Fuzzy logic in arrhythmia detection: A systematic review of techniques, applications and clinical interpretability

Abstract

Accurate and interpretable arrhythmia detection is essential for timely diagnosis and intervention, especially in medical decision support systems (MDSS). Fuzzy logic, known for its ability to handle uncertainty and improve interpretability, has emerged as a promising approach. This systematic literature review (SLR) examines the role of fuzzy logic in advancing arrhythmia detection, focusing on accuracy, interpretability, and integration with computational intelligence. Following PRISMA guidelines, 18 studies published between 2019 and 2024 were analyzed to address four key questions: (Q1) the accuracy and reliability of fuzzy logic systems, (Q2) the effectiveness of hybrid systems combining fuzzy logic with computational intelligence, (Q3) the challenges in developing multi-class fuzzy logic systems, and (Q4) the impact of fuzzy logic on interpretability in MDSS. Techniques such as Adaptive Neural Fuzzy Inference Systems (ANFIS) and hybrid models with neural networks and bio-inspired algorithms were evaluated. ANFIS demonstrated near-perfect accuracy, while hybrid systems improved scalability and overcame the challenges of multi-class classification. Limitations included reliance on benchmark datasets, limited real-world validation, and insufficient focus on Explainable Artificial Intelligence (XAI). Fuzzy logic shows great potential for developing interpretable and robust MDSS for arrhythmia detection. Future research should prioritize advancing XAI, incorporating diverse data sets, and addressing real-world challenges to improve clinical applicability.

1. INTRODUCTION

Cardiac arrhythmias are a critical category within cardiovascular disease (CVD), contributing to approximately 21 million deaths worldwide each year (World Heart Federation, n.d.). These conditions are classified as high-risk cardiac pathologies, which often lead to serious cardiovascular events such as sudden cardiac death and stroke (Srinivasan & Schilling, 2018). Arrhythmias are characterized by irregular heartbeats that indicate abnormal electrical activity within the cardiac nervous system or heart anatomy (Fu, 2015). Understanding the etiology, progression, and management of arrhythmias is critical because of their profound impact on cardiovascular morbidity and mortality (Krittanawong et al., 2023). Medical decision support systems (MDSS) are essential tools for improving the diagnostic accuracy of cardiac arrhythmias. Artificial intelligence (AI)-based MDSS have the potential to significantly improve the accuracy and efficiency of arrhythmia detection and classification (Menaceur et al., 2023). Despite their potential, implementation of these systems is challenging, as users often struggle to interpret complex results and algorithmic recommendations, hindering their effective integration into clinical practice (X. Chen et al., 2022). Patients often find it difficult to understand their arrhythmia risk profile when confronted with abstract numerical clinical data, hindering informed decision making and adherence to prescribed treatments (Jamthikar et al., 2022).

Numerous studies have investigated arrhythmia classification, often summarized in comprehensive reviews. Machine learning techniques dominate this field, with an emphasis on novel approaches to improve model quality and generalization (Ardeti et al., 2023; Huang et al., 2024). Deep learning differs from traditional machine learning in its ability to process large datasets accurately, making it the preferred choice for arrhythmia classification (Ansari et al., 2023; Xiao et al., 2023). However, these models often obfuscate decision-making and reduce patient and physician confidence, as even statistical methods struggle to adapt to new data inputs. Fuzzy logic, which leverages uncertainty in decision-making, has proven valuable for monitoring diagnoses and assessing risk levels (Farhan et al., 2018). In addition, fuzzy logic is inherently interpretable, providing a transparent alternative to conventional methods.

A growing body of literature proposes fuzzy logic as a promising solution to address these interpretability challenges. Known for its ability to model imprecise and ambiguous information, fuzzy logic has gained attention as a potential solution. Fuzzy logic bridges the gap between technical performance and clinical usability by transforming numerical data into linguistically meaningful terms. This approach improves both the accuracy and the interpretability of arrhythmia detection systems, thus meeting the dual needs of clinicians and patients (Arief Kanza et al., 2024; Le et al., 2023).

Existing reviews often examine isolated aspects of fuzzy logic or AI in MDSS. However, a comprehensive analysis linking interpretability, hybrid systems, and practical clinical use is still lacking.

This review examines the use of fuzzy logic systems for arrhythmia detection, focusing on their accuracy, hybrid methods, development challenges, and contributions to interpretability. Insights from this analysis aim to guide the development of effective, explainable, and reliable fuzzy logic-based arrhythmia detection systems to improve healthcare outcomes.

This research aims to provide a comprehensive systematic literature review (SLR) of fuzzy logic applications in arrhythmia detection. It addresses specific technical issues while considering the broader implications of these technologies for clinical practice.

This review critically examines fuzzy logic applications in arrhythmia-focused MDSS using the PRISMA protocol. It highlights the uses, benefits, challenges, and integration of fuzzy logic with other computational intelligence techniques in cardiac MDSS.

2. BACKGROUND

2.1. Medical decision support systems for arrhythmia

The cardiovascular system, including the heart, arteries, veins, and capillaries, provides adequate blood flow. Cardiac arrhythmias result from irregular heartbeats characterized by excessively slow or rapid rhythms caused by faulty electrical impulses (Sahoo et al., 2020). As shown in (Fig. 1), there are two primary types: atrial and ventricular. Normal heart rhythm is generated and controlled by the cardiac conduction system, which includes the sinus node, atrioventricular node, and HIS-Purkinje system. Arrhythmias include Supraventricular arrhythmias (SVAs) and ventricular arrhythmias (VAs) (Garikapati et al., 2022).

AF, which originates in the atria, disrupts the upper chambers of the heart and can lead to thromboembolic events and increased cardiovascular morbidity and mortality. Atrial fibrillation (AFib) is the most common form, affecting 2.5 million Americans (National Heart, Lung, and Blood Institute, 2022). Atrial flutter, a less severe form, can pose significant risks (Vila et al., 2021).

Ventricular Arrhythymias originating in the lower chambers of the heart pose a greater risk to patient safety and require immediate medical intervention. Accurate diagnosis, risk stratification, and management are critical (Imburgio et al, 2024).

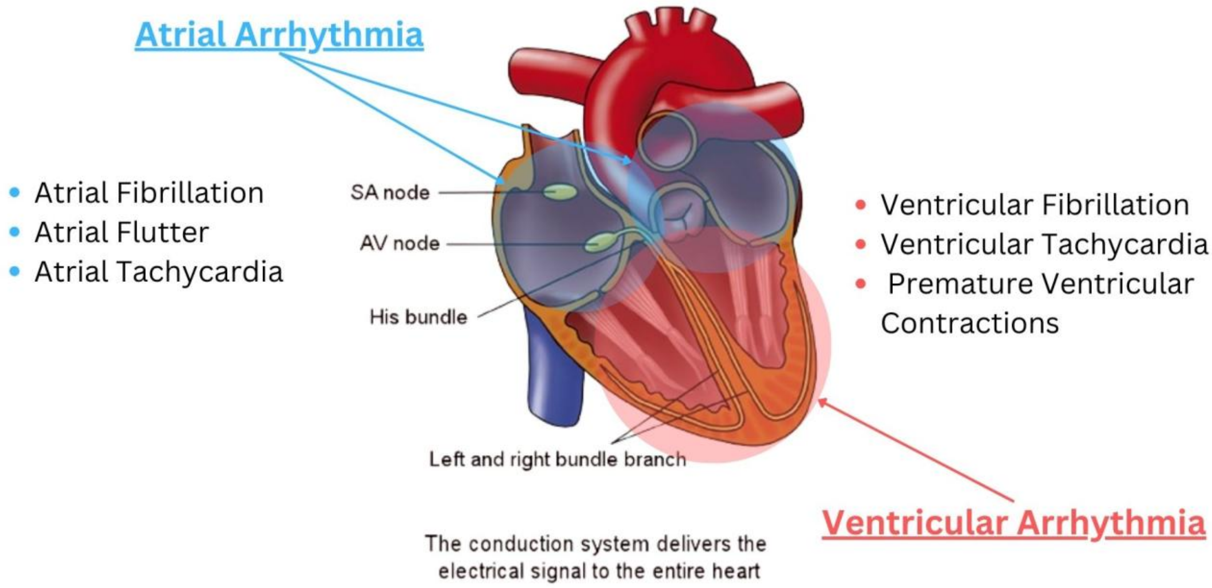

Fig. 1. Classification of atrial and ventricular arrhythmias in the heart

An electrocardiogram (ECG) signal provides a comprehensive picture of the heart's function and electrical activity, allowing the identification and analysis of cardiac arrhythmias (Ratnaparkhi et al., 2021). ECG monitoring facilitates the identification and categorization of different types of arrhythmias, allowing healthcare professionals to develop effective treatment strategies (Menaceur et al., 2024).

ECG features and clinical information have accelerated AI research in arrhythmia classification using machine learning and deep learning techniques (Moreno-Sánchez et al., 2024). These methods have demonstrated high accuracy, and several models have been integrated into MDSS for arrhythmia diagnosis. Machine learning models use statistical techniques to analyze ECG features and generate predictions. Convolutional Neural Networks (CNNs) autonomously extract complex patterns from ECG signals, eliminating the need for manual feature selection (Ardeti et al., 2023; Vásquez-Iturralde et al., 2024). As data-driven diagnostic systems based on machine learning and deep learning models have become more popular, real-time protection systems for continuous cardiac monitoring have emerged. These systems focus on arrhythmias and heartbeat irregularities. The scope of arrhythmia detection has expanded to include the Internet of Medical Things (IoMT) and lightweight, non-invasive devices (Opoku Agyeman et al, 2022; Xiao et al, 2023).

To improve the interpretability and accuracy of MDSS, fuzzy logic has emerged as a promising computational approach that effectively bridges the gap between complex data outputs and clinical usability.

2.2. Fuzzy logic theory for decision making

Fuzzy logic, introduced by Zadeh (1965) is a soft computing paradigm that allows reasoning with degrees of truth rather than binary evaluations, as shown in (Fig. 2). Fuzzy logic addresses the imprecision and uncertainty inherent in natural language and various application domains by accepting imprecise solutions, thus allowing for more nuanced and human-like decision making in computing (Zadeh, 1975).

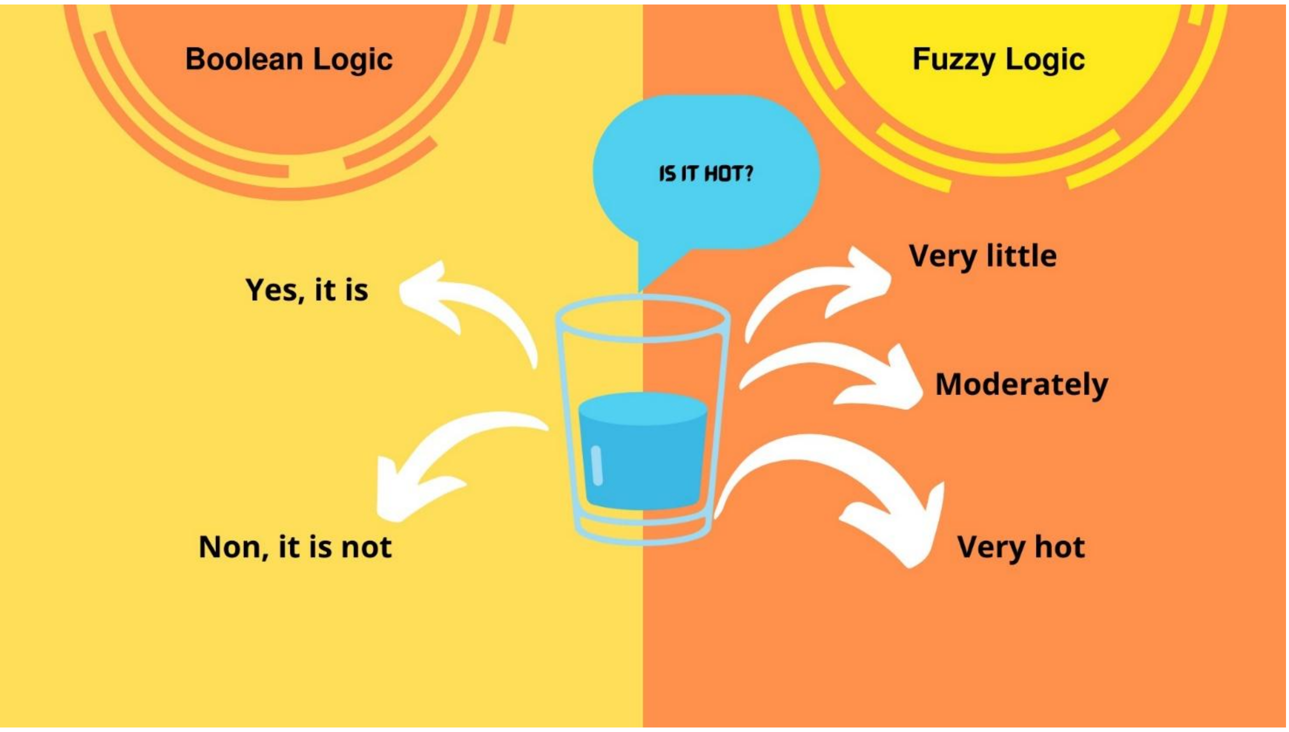

Fig. 2. Comparison between boolean logic and fuzzy logic for decision making

Fuzzy inference is a fuzzy logic reasoning process that generates outputs based on fuzzified inputs, using IF-THEN rules and fuzzy rules to specify the implication between condition and conclusion rule components. Fuzzy inference is a method that uses fuzzy logic to map input to output, providing a basis for decision-making or pattern recognition (Ahmadi et al., 2018; Kouah Sofia, 2017). Two main types of Fuzzy Inference Systems (FIS) are Mamdani-type (1977) (Mastacan & Dosoftei, 2018) and Takagi-Sugeno-type (1985) (Ying, 1998).

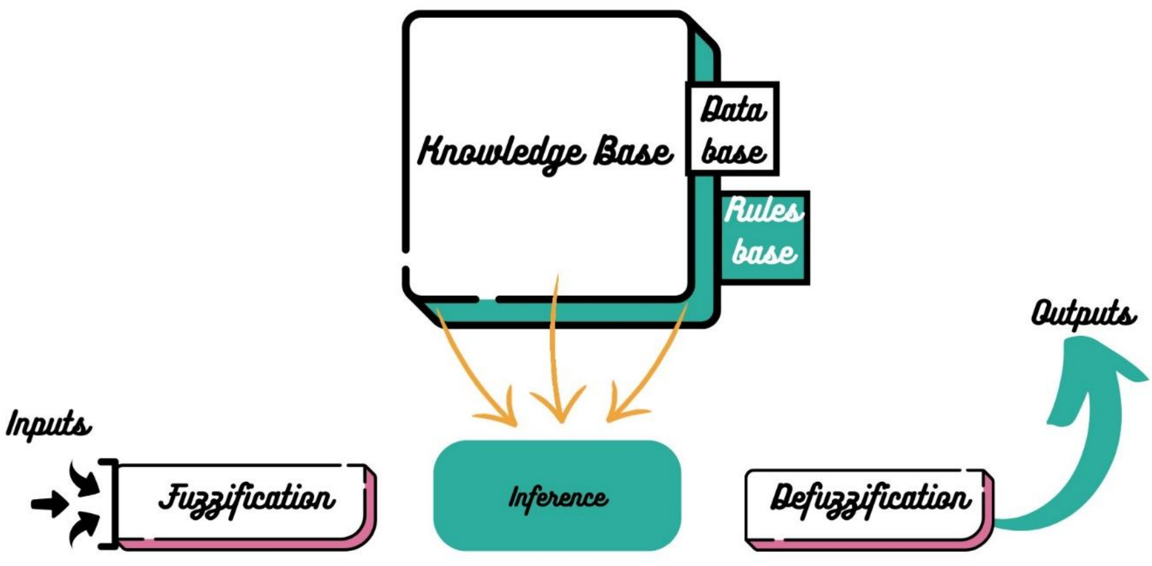

Fig. 3. Fuzzy logic system architecture: From inputs to outputs

Figure 3 illustrates that the FIS consists of five key components: a database, a fuzzy rule base, a fuzzification component, a fuzzy inference engine, and a defuzzification component. The fuzzy model knowledge base consists of fuzzy sets and rules that fuzzify the crisp inputs of the model. The system outputs are produced by defuzzifying the fuzzy solution surface generated by executing the rule base.

A membership function assigns a degree of belonging to points within an input space, indicating their membership intensity within a fuzzy set. It must transition seamlessly from 0 to 1, and its design prioritizes simplicity, efficiency, and speed. X and its elements x represent a fuzzy set within a given discourse universe, and each element is associated with a membership level ranging from 0 to 1. Selecting appropriate membership functions is critical to rule activation and resulting actions, and fuzzy logic becomes more powerful when integrated with other AI algorithms (Rizvi et al., 2020; Zhang & Qin, 2022).

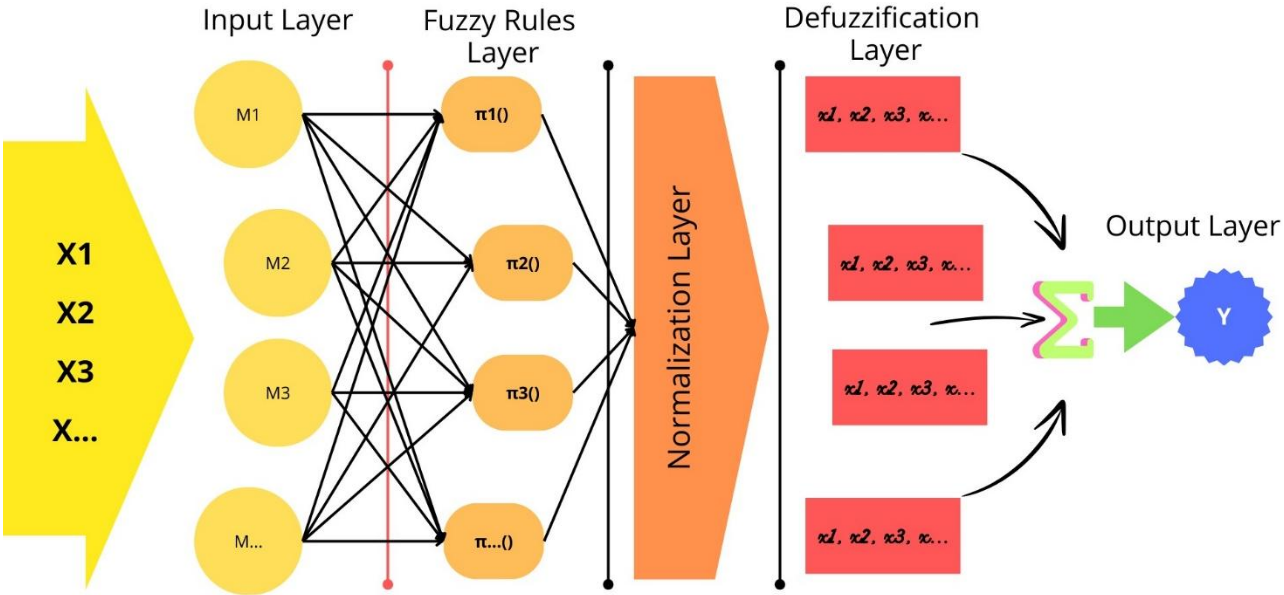

Fig. 4. Structure of a fuzzy inference system with input and output layers

The ANFIS is a robust hybrid algorithm that combines fuzzy logic with artificial neural network (ANN) models (Onyelowe et al., 2021). This approach addresses the uncertainty inherent in all medical disciplines, from diagnosis to treatment. ANFIS, developed by Jang in 1995 (Onyelowe et al., 2021) ANFIS leverages the adaptive learning capabilities of ANNs with the precision of FIS, mirroring the Takagi-Sugeno fuzzy model. Jang designed ANFIS to navigate and model the behavior of complex, ill-defined systems, effectively addressing engineering challenges. In (Fig. 4) The structure of ANFIS includes five layers (Lin et al., 2023): An input layer, a fuzzy rules layer, a normalization layer, a defuzzification layer, and an output layer. Layer 1 is an adaptive node with membership functions such as a generalized bell and a Gaussian; Layer 2 indicates the firing strength of a rule; Layer 3 indicates the normalized firing strength of each rule; and Layer 4 contains a node function that indicates the contribution of rules to the overall output.

3. METHODOLOGY

This study adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, a well-established framework for ensuring rigor and transparency in systematic reviews. This study adapts the PRISMA protocol to explore comprehensively the application of fuzzy logic in arrhythmia diagnosis within the MDSS, with the aim of improving the interpretability of the results for clinical practitioners (Ahmadi et al., 2018). To guide this review, specific research questions were formulated that address arrhythmia detection, cardiac abnormality identification, and heartbeat classification through the lens of fuzzy logic systems. These questions are intended to provide insights into the effectiveness, accuracy, and interpretability of fuzzy logic-based approaches to arrhythmia diagnosis:

Q1: Compare the accuracy and reliability of fuzzy logic systems and techniques for arrhythmia detection.

Q2: What is the effectiveness of hybrid systems that integrate fuzzy logic with other computational intelligence methods?

Q3: Challenges and opportunities in developing multi-classifier fuzzy logic systems for comprehensive arrhythmia detection.

Q4: How does fuzzy logic contribute to the interpretability and explainability of arrhythmia classification models, and what are its implications for clinical decision support systems?

We follow the guidelines of the PRISMA checklist (Page et al., 2021) tailored to our research purpose and technical perspective. A multi-faceted search strategy was developed to ensure a comprehensive and systematic review, utilizing major academic databases such as Science Direct, Springer, IEEE Xplore, ACM Digital Library, and Google Scholar. This approach uses carefully constructed search strings that use Boolean operators to identify relevant studies. Three components make up the structure of the search string:

("cardio arrhythmias" OR "cardiac arrhythmias" OR "heart arrhythmias") AND ("fuzzy logic" OR "fuzzy systems" OR "fuzzy inference") AND ("classification" OR "detection" OR "diagnosis").

The methodology includes three key components: the first defines the specific cardiac pathology under study, the second emphasizes medical data-driven systems based on fuzzy logic, and the third addresses critical aspects of AI aligned with our research goals. The literature search spans from 2019 to 2024 to include the latest advances in the field, coinciding with the COVID-19 pandemic, a catalyst for accelerated research in AI-MDSS. These systems have gained prominence for their potential to improve patients' understanding of their health status, a critical factor in remote healthcare management. The post-2019 focus allows for an exploration of the impact of the pandemic on the development and application of fuzzy logic in arrhythmia diagnosis and patient-centered healthcare solutions.

3.1. Eligibility criteria

The inclusion criteria included studies published in peer-reviewed scientific journals or international conferences, written in English, published from 2019 to date, in engineering, computer science, medical or biomedical fields, focusing on arrhythmia as a pathology, using fuzzy logic in data-driven systems, research papers, simulations, experimental or comparative studies, conducted on human subjects, The following are excluded: unpublished studies, with the exception of peer-reviewed journals/conferences, studies that do not apply fuzzy logic techniques to arrhythmia diagnosis, that do not report experimental results or performance evaluations, review articles, surveys, opinions, case studies without original research, studies that focus only on hardware without algorithmic details, duplicate studies with overlapping data sets, articles with inaccessible or incomplete full-text information, and studies conducted on non-human subjects.

3.2. Search strategy

A customized search strategy was used across multiple electronic databases to identify studies on cardiac arrhythmias and fuzzy logic techniques within the fields of computer science and engineering. Search results were filtered to include English-language studies relevant to the specified areas. Articles retrieved were organized using Zotero (2025) an open source research management tool that facilitates efficient collection, categorization, and evaluation. The selection process included an initial screening of titles and abstracts to assess relevance and potential bias, followed by a detailed review of full texts for inclusion in the final dataset.

3.3. Risk of bias assessment

To assess methodological quality and potential risk of bias across studies, we used a structured quality assessment framework with four key criteria:

1. Data Set Representativeness,
2. Validation methodology,
3. Baseline comparisons,
4. Statistical performance reporting.

These criteria were selected to reflect the most critical issues affecting the reliability and generalizability of fuzzy logic-based AI models in healthcare. Each study was independently assessed by two reviewers using a standardized scoring rubric aligned with these criteria. Discrepancies in scoring were resolved by consensus-based discussion to ensure consistency and objectivity of judgment.

Special attention was given to the implementation phase of fuzzy logic, evaluating how fuzzy techniques were integrated into the AI workflow, whether in the feature fusion, inference, or interpretability layers.

The studies were then categorized into three quality levels (high, medium, and low) based on cumulative scores:

- High-quality studies demonstrated the use of real-world clinical datasets, implemented robust validation strategies (e.g., k-fold cross-validation), and reported comprehensive performance metrics.
- Moderate quality studies showed partial adherence to rigorous methodologies, often used moderately representative datasets, or omitted clear baseline comparisons, although they typically attempted comparative benchmarking with existing methods.
- Low-quality studies were characterized by methodological limitations, including small or synthetic datasets, lack of meaningful comparisons, and superficial validation efforts.

4. RESULTS

4.1. Studies selection

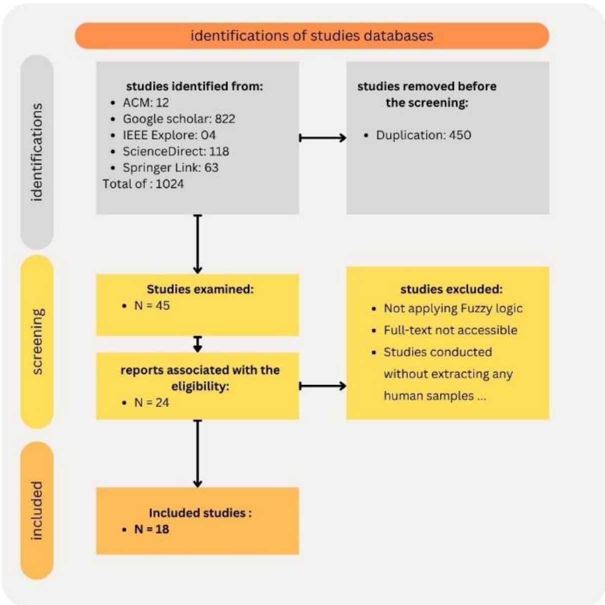

Fig. 5. PRISMA flowchart for our systematic reviews included searches of databases

The systematic review followed a structured selection process, including identification, screening and eligibility assessment, as shown in (Fig. 5). The initial database search identified 1,024 references, which were reduced to 93 records after the screening phase. The remaining 45 papers were assessed for content relevance, resulting in 24 studies qualifying for full-text review and detailed analysis; insufficient information or failure to meet eligibility requirements led to the exclusion of two papers. The systematic review selected a final set of 18 studies that were deemed relevant to the objectives of the study and provided critical evidence to address the research questions.

4.2. Study characteristics

To provide an overview of the selected research papers, (Table 1) presents the technical details with a special focus on fuzzy parameters and the performance achieved by the models. This table provides a clear insight into the methodologies used in the studies. The "Interpretability Measure" is a critical feature of fuzzy logic systems that distinguishes them from "black box" models and facilitates human understanding and interpretation of decision processes. - Linguistic Rule Clarity (LRC): Allows rules to be expressed in clear, natural language for improved usability. - Feature Relevance Transparency (FRT): Highlights the importance and role of individual ECG features in the decision process. - Decision Path Traceability (DPT): Provides transparency by allowing the decision process to be easily traced. - Uncertainty Representation (UR): Provides a structured explanation of classification uncertainty levels, improving confidence and understanding.

Tab. 1. SLR Summary of fuzzy logic applications in arrhythmia detection: Techniques, datasets, and performance metrics. NSR: Normal Sinusal Rhythm, AFib: Atrial Fibrillation, LBBB or RBBB: Left or Right Bundle Branch Block, AE: Atrial Ectopy, VE: Ventricular Ectopic, VFib: Ventricular Fibrillation, AFL: Atrial Flutter, SVC: SupraVentricular Contraction

Study ID	Authors (Year)	Fuzzy Logic Technique	Hybrid Approach	Interpretability Measure	Arrhythmia Types	Dataset	Performance Metrics (%)
S01	Madinatou et al. (2019)	ANFIS	Fuzzy + ANN	FRT	NSR, AFib, LBBB, RBBB, AE, VE	MIT-BIH Arrhythmia Database	Acc = 99.7, Sp = 100, Se = 98
S02	Corona-Figueroa et al. (2019)	ANFIS	Fuzzy + ANN	FRT	Foetal Arrhythmias	Lieven De Lathauwer Dataset	Acc = 88.88
S03	Mandal et al. (2021)	ANFIS	Fuzzy + ANN	DPT	NSR, AFib, Vfib, AFL	MIT-BIH Arrhythmia Database	Acc = 99.88, Se = 99.98, Pr = 99.90
S04	Swetha & Ramakrishnan (2021)	K-means clustering optimized fuzzy logic control algorithm	Fuzzy + K-means clustering	FRT, LRC, UR	Several types of Arrhythmia groups	MIT-BIH Arrhythmia Database	Acc = 91.5
S05	Al-Naami et al. (2022)	ANFIS	Fuzzy + ANN	FRT	LBBB	MIT-BIH Arrhythmia Database	Acc = 99.81, Se = 99.88, Sp = 100
S06	Li et al. (2022)	Taguchi-based convolutional neuro-fuzzy network (1D-TCNFN)	Fuzzy + CNN	DPT	17 arrhythmia	MIT-BIH Arrhythmia Database	Acc = 93.95, Se = 96.03, Sp = 93.47, F1 = 94.30
S07	Rahman et al. (2023)	FIS	Fuzzy System	FRT, LRC, LRC	4 degrees of Arrhythmias	MIT-BIH Arrhythmia Database	Acc = 100 (validation)
S08	Taher et al. (2023)	FIS + KNN	Fuzzy Features Selection + KNN	/	16 arrhythmia	UCI cardiac arrhythmia	Acc = 98.9
S09	Waseem et al. (2023)	ANFIS	Fuzzy + ANN	FRT	SNR or Arrhythmia	PTB Diagnostic ECG Dataset, MIT-BIH Arrhythmia Database	Se = 98.3, Sp = 97.8, F1 = 98
S10	Huang et al. (2022)	Sorting Fuzzy Min-Max (SFMM)	Fuzzy	FRT, DPT, LRC, LRC	AFib	Private Dataset	Acc = 91.67
S11	H. Chen et al. (2022)	Fuzzy c-means (FCM) clustering	Fuzzy	DPT, LRC	AVs	PTB Diagnostic ECG Dataset, CU Ventricular Tachyarrhythmia Dataset	Acc = 98.4, Se = 97.5, Sp = 99.1
S12	Premalatha et al. (2024)	ANFIS + Grasshopper optimization algorithm	Fuzzy + Bio-inspired	DPT	AVs	MIT-BIH Arrhythmia Database	Acc = 96, Se = 95, Pr = 97, F1 = 96
S13	Madhura et al. (2024)	ANFIS	Fuzzy + ANN	DPT	SNR or Arrhythmia	MIT-BIH Arrhythmia Database	Acc= 99.82, Se=98.42, Sp= 98.63
S14	Lakshmi Devi et al. (2021)	ANFIS	Fuzzy	LRC	Normal or Arrhythmia	MIT-BIH Arrhythmia Database,	Acc = 94.22, RMSE = 0.496034
S15	Abagaro et al. (2024)	ANFIS	ANFIS + discrete wavelet transform (DWT)	FRT, LRC	SNR, LBBB, RBBB, SVC	MIT-BIH Arrhythmia Database	Acc = 99.44, Se = 99.36, Sp= 99.84
S16	Alshahrani et al. (2024)	Intuitionistic Fuzzy Logic Controller (IFLC)	Fuzzy	LRC, UR, DPT	Bradycardia	Simulated test cases: 6 patients (age 45–66) tested at rest, walking, jogging; no external dataset used	RMSE: 0.17–0.26 Max Error: 0.49–2.38%
S17	Mújica-Vargas et al. (2024)	Intuitionistic Fuzzy Clustering (IFC) + Recurrence Plots	IFC for signal transformation + Deep CNN models	LRC, UR, DPT	SNR, LBBB, RBBB, PVC	MIT-BIH Arrhythmia Database	Acc = 98.00, Se = 98.00, Pr = 98.00, F1 = 98.00, Sp = 99.60
S18	Ramirez et al. (2019)	Type-1 FIS & Interval Type-2 FIS	Fuzzy KNN + MLP-GDM + MLP-SCG Combined via T1-FIS and IT2-FIS	LRC, DPT, UR	SNR, LBBB, RBBB, PVC, FPN, AP, AAP, FVN, VE, P	MIT-BIH Arrhythmia Database	Acc = 94.20

4.3. Related works

Fuzzy control systems (FCS) apply fuzzy logic to decision making, using linguistic variables to interpret input data. S04 (Swetha & Ramakrishnan, 2021) proposed a dual FCS classifier for six arrhythmia types, combining features such as mean average, heart rate, variability, and amplitude, with performance enhanced by K-nearest neighbor (KNN) integration after ECG preprocessing and R-peak detection.

Building on this foundation, S07 (Rahman et al., 2023) Extends this with an eight-feature linguistic FCS embedded in an IoT cloud framework, supporting real-time monitoring and preprocessing for four-level arrhythmia classification. S08 (Taher et al., 2023) introduced a two-layer FIS (MIN and MAX) for feature selection using four mathematical methods. The selected features were tested across classifiers, with KNN performing best for 16 arrhythmia types on the UCI dataset.

S10 (Huang et al., 2022) Advanced the field by developing an embedded system using an improved sorting fuzzy min-max model that explicitly targets AFib detection by ECG sensors, encompassing the entire pipeline from data acquisition to decision making. In addition, S11 (H. Chen et al., 2022) investigated unsupervised classification methods for VA using soft clustering techniques. This approach uses fuzzy c-means clustering, driven by J-index results derived from phase-space analysis of 5-second ECG segments, to generate four-dimensional fuzzy feature sets. The methodology demonstrated exceptional performance metrics compared to current approaches, and its robustness was validated on diverse datasets.

S16 (Alshahrani et al., 2024) presents a novel Intuitionistic Fuzzy Logic Controller (IFLC) for heart rate control in implanted dual-sensor pacemakers, targeting patients with bradycardia. The innovation lies in the use of IFL, which extends traditional fuzzy logic by incorporating non-membership functions and an uncertainty (hesitancy) component. This structure enables the controller to more effectively model imprecise, uncertain medical knowledge and allows the integration of cardiologist expertise into the rule-based system.

The integration of deep learning with fuzzy logic has proven to be highly effective in arrhythmia classification. S06 (Li et al., 2022) proposed a hybrid model that combines convolutional layers with neuro-fuzzy layers via a fusion mechanism using four different feature fusion methods. This design utilizes CNNs for robust feature extraction while enhancing sensitivity through fuzzy-based adaptive classification.

The ANFIS framework is notable for merging neural network learning with fuzzy inference systems. Numerous studies (S01 (Madinatou, 2019), S03 (Mandal et al., 2021), S05 (Al-Naami et al., 2022), S09 (Waseem et al., 2023), S12 (Premalatha et al., 2024), S13 (Madhura et al., 2024), S14 (Lakshmi Devi et al., 2021)) have applied ANFIS to arrhythmia classification with strong results. In particular, S01 compared FIS, ANN, and ANFIS and reported superior accuracy (99.8%) on the MIT-BIH dataset. Beyond adult diagnostics, S02 (Corona-Figueroa, 2019) S03 extended ANFIS to fetal arrhythmia detection, demonstrating its adaptability to different clinical contexts. S03 focused on differentiating fibrillation from flutter using 30 ranked features and evaluated ANFIS performance against various machine learning classifiers. S05 targeted LBBB detection using QRS feature fusion and ANFIS modeling, outperforming other LBBB methods. S15 extended classification to RBBB and SVC using DWT extracted features and PCA for dimensionality reduction, achieving 99.44% accuracy. The model also incorporated fuzzy linguistic levels to improve interpretability using MATLAB's Fuzzy Logic Toolbox.

A comprehensive comparative analysis is presented in S09 that evaluates the relative performance of ANN, CNN, and ANFIS algorithms for arrhythmia classification using the MIT-BIH dataset. The empirical results demonstrate the superior performance metrics of ANFIS over alternative methods.

S13 advances the field by developing an Internet of Things (IoT)-based evaluation framework that emphasizes sophisticated ECG signal processing techniques. The implementation explicitly uses Sugeno ANFIS, which was selected for its computational efficiency, mathematical rigor, adaptability, and optimization capabilities.

S12 presents a sophisticated hybrid solution that integrates fuzzy logic with the Grasshopper optimization algorithm to enhance the performance of ANFIS classifiers. This innovative approach achieves 96% classification accuracy by optimizing network parameters and implementing advanced feature extraction techniques. The methodology demonstrates robust handling of ECG signal variability while improving the accuracy of arrhythmia detection.

Similar to S16, study S17 proposes a novel method for multiclass arrhythmia classification that integrates Intuitionistic Fuzzy Clustering (IFC) with Recurrence Plot (RP) generation. The key innovation lies in transforming ECG signals into intuitionistic fuzzy domain representations that capture both membership and non-membership values, along with an uncertainty (hesitancy) index. This leads to recurrence plots that visually express signal dynamics, which are then used as inputs to various CNN architectures (GoogleNet, Xception, DenseNet).

Finally, a new technique that combines multiple fuzzy models is presented in S18, where a hybrid arrhythmia classification system combines three classifiers: Fuzzy KNN, Multilayer Perceptron (MLP) with

Gradient Descent and Momentum (GDM) and MLP with Scaled Conjugate Gradient Backpropagation (SCG) in a modular two-lead architecture, with classification fusion via both Type-1 Fuzzy Inference Systems (T1-FIS) and Interval Type-2 Fuzzy Inference Systems (IT2-FIS).

4.4. Synthesis of results

Table 2 summarizes recent research on the application of fuzzy logic and related AI methodologies to arrhythmia diagnosis. Each study emphasizes different methodologies, including model comparisons, feature selection techniques, and implementation in real-time systems. Each technique has identified limitations, with common issues including the need for extensive validation, improved accountability, and diverse data sources for better generalization across patient demographics. This review provides a basis for understanding existing deficiencies and opportunities for improvement in arrhythmia detection techniques.

Tab. 2. Summary of studies on fuzzy logic in arrhythmia detection: Technology and limitations

Study ID	Fuzzy logic technology	Limitations
S01	The study emphasizes data preparation and achieves good fitting by using only triangular membership functions applied to multiple morphological features.	The study would benefit from experimentation with additional parameters, such as different membership functions and alternative datasets for validation. Reliance on morphological data alone is insufficient; frequency domain features could improve performance. In addition, the work lacks deployment and clinical validation, which are critical to ensuring interoperability and real-world applicability.
S02	The study uses two fuzzy rules derived from a first-order Sugeno model using four membership functions.	The study requires a larger dataset for training and could benefit from a stronger focus on the interpretability of the classification results. In addition, the creation of a deployable, lightweight application would improve practical usability.
S03	The study provides an overview of the ANFIS model but does not specify parameter values or implementation details.	The study compares the model with traditional machine learning methods rather than deep learning approaches. It lacks clarity in the classification and training steps and provides limited details about the validation phase. Additionally, advancing the model to the deployment stage would enhance its practical applicability
S04	The study employs two traditional FCSs, each using different input combinations. The method is based on seven linguistic interpretation levels and Gaussian membership functions.	The method requires a larger data set as no validation set was used. While the study creates linguistic fuzzy sets, it focuses only on the accuracy of the system without addressing the interpretability that could benefit the approach. In addition, the system needs to be optimized and validated by clinical experts, as well as monitored in the real world to improve its explainability.
S05	The ANFIS model uses five inputs with five rules for a Sugeno FIS. After 200 epochs, it achieves an accuracy of 99.87%.	The authors acknowledge that the study is limited by the lack of use in embedded systems, insufficient focus on accountability, and lack of clinical validation.
S06	The study introduces a novel neural network structure that integrates convolutional layers with neuro-fuzzy layers using four types of fusion methods. It employs the Taguchi method, where fuzzy rules serve as parameters of the system.	While the method demonstrates high performance, it requires more data sets for validation and comparisons with different structures to substantiate the results. The work lacks interpretability and does not include application or clinical validation.
S07	The study used an FCS with only three membership functions for the eight features. The focus was on creating a lightweight model suitable for direct use in IoT devices.	The study covers several aspects of the framework, from data acquisition to decision making and final monitoring. However, it requires more data diversity and the inclusion of additional important features, such as time-domain characteristics of ECG recordings. In particular, the study lacks clinical validation.
S08	The study used an FIS for feature ranking, where the inputs were statistical measurements of the ECG features. The system used trapezoidal membership functions with two levels to achieve effective feature selection.	The FIS could be enhanced with additional fuzzy sets and methods. The system needs more emphasis on interpretability and explainability. In addition, the study lacks generalization considerations, validation, and clinical application, making it similar to comparative studies.
S09	The study uses a simple ANFIS structure with four rules and Gaussian membership functions.	The study is purely comparative and experimental, with no additional novel contributions.
S10	The study develops an improved fuzzy min-max method by adding a sorting layer that takes into account the input order. It uses a hyperbox data structure for each label, effectively creating a fuzzy neural network.	While the study presents a novel method with high accuracy, it requires more attention to explainability. The method is sophisticated but lacks a validation step and clinical trials. In addition, the implementation phase is not addressed and more focus is needed on the monitoring phase.
S11	The study presents an unsupervised fuzzy clustering technique, focusing on the data preparation and feature extraction phases. Overall, it demonstrates the effectiveness of fuzzy c-means clustering for arrhythmia classification.	The study is well structured, with a clear explanation of the steps of the approach and the use of different datasets to validate the work. However, the approach needs more emphasis on clinical validation and real-world application, as it requires significant computational resources for data preparation.
S12	The fuzzy inference system applies rules to these inputs to evaluate the severity of the arrhythmia, producing classifications ranging from normal to severe.	Limitations of the study include reliance on high-quality ECG data, increased computational complexity, and challenges in generalization and interpretability. Further research is needed to improve robustness and applicability in different clinical settings.
S13	The study specifies the use of Sugeno FIS, but does not provide details on ANFIS parameters.	The study validates the approach using well-known methods such as cross-validation and compares it with other studies. However, further clinical validation is needed. Although it claims to be efficient, it lacks a description of the deployment phase and its suitability for embedded systems.
S14	Presents an ANFIS for the classification of cardiac arrhythmias using heart rate variability features derived from ECG signals. The model demonstrated superior classification accuracy compared to the Support Vector Machine (SVM) classifier.	It evaluates performance using only accuracy as a metric, compares the ANFIS model only to SVM, lacks a detailed explanation of the feature selection process, and provides no insight into the interpretability of the model's decisions.
S15	The study presents a highly accurate ANFIS Sugeno model using features extracted via DWT. A key strength of the study lies in its interpretability, which is achieved through the use of linguistic membership functions "small", "medium", "large" and feature contributions for explainability.	The study covers fuzzy logic using ANFIS, but the evaluation lacked real-world experimentation or deployment. The data set had limited variability and the results did not effectively address risk estimation. This reduces the interpretability of the study.

Tab. 2. Summary of studies on fuzzy logic in arrhythmia detection: Technology and limitations, continued

Study ID	Fuzzy logic technology	Limitations
S16	The IFLC provides a transparent, interpretable decision-making process using linguistic rules, input-output fuzzification schemes, and rule traceability. It adapts pulse duration based on patient activity, demonstrating low RMSE and minimal control error. Compared to classical methods such as Fuzzy, Fuzzy PID and RBF based methods.	The limitations of an AI-driven IFLC heart rate control system designed to control heart rate under bradycardia conditions that does not perform classification across multiple arrhythmia types. The system also lacks interpretability and explainability, with no transparency of feature relevance and scalability issues. In addition, the IFLC is not integrated with deep learning or neuro-fuzzy approaches, which may underperform on dynamic, non-linear ECG data or patient-specific variations compared to models such as deep neuro-fuzzy networks or hybrid LSTM-fuzzy architectures.
S17	IFC extends traditional fuzzy sets by introducing non-membership and hesitation, improving the system's ability to manage ambiguity in ECG signals. recurrence plots provide visually interpretable representations of ECG dynamics.	The proposed method has limitations such as lack of feature attribution, black-box deep learning dependency, model adaptability, and computational overhead of recurrence plot generation. It does not satisfy FRT and black-box deep learning dependencies and may not adapt to new ECG signal types or patient profiles. Alternatives include neuro-fuzzy models or metaheuristically tuned fuzzy networks.
S18	The modular classification fusion strategy per ECG lead. The use of manual, expert-driven fuzzy rule bases to fuse classifier outputs. Demonstration that IT2-FIS improves performance over T1-FIS by better modeling uncertainty and ambiguity in classifier decisions. The system achieves 94.30% accuracy on a 2-lead ECG input from MIT-BIH, outperforming previous fuzzy and ML-based classifiers.	The fuzzy inference system fuses only classifier outputs, not features. Rule bases are manually constructed, which limits scalability and adaptability. Training and testing the hybrid ensemble plus fuzzy fusion layers involves multiple models per lead, which increases computational cost and may be less suitable for embedded or edge devices without further optimization.

5. DISCUSSION

This SLR on fuzzy logic in arrhythmia detection identifies several trends, strengths and limitations in the existing research corpus. By analyzing the main concepts, performance indicators, and limitations within the reviewed studies, we can highlight essential aspects that guide the future trajectory of this domain.

5.1. Comparative analysis of fuzzy logic techniques (Q1)

Our quality assessment framework, which is based on validation methodology and the fuzzy logic implementation phase, reveals substantial variation in methodological rigor across the 17 studies reviewed. Studies with the highest quality scores used real-world clinical datasets and demonstrated robust cross-validation protocols with comprehensive performance reporting (S11, S02, S12). These high-quality studies consistently validated their approaches using authentic clinical records, providing stronger evidence of real-world applicability (S10, S16).

In contrast, medium-quality studies (S01, S06, S07, S08, S09, S13, S15, S17) had limitations in data set representativeness and baseline comparisons, thus achieving lower quality scores. However, these studies attempted to improve their validation credibility by incorporating comparative analyses with advanced deep learning methods, which is a positive step towards comprehensive benchmarking. Conversely, low-quality studies demonstrated significant methodological shortcomings by using limited datasets and basic machine learning comparisons. Despite reporting positive results, these approaches raise validation concerns given the rapid advancement of contemporary AI methodologies (S03, S04, S05, S14, S18).

The implementation of fuzzy logic varies widely across studies, with some using fuzzy systems for feature fusion (S08), while others focus on output interpretation such as risk categorization. This variation in quality directly correlates with accuracy ranges, with higher quality studies consistently achieving >95% classification accuracy using fuzzy classifiers, suggesting that methodological rigor has a significant impact on the reliability of performance claims.

The analysis of the reviewed studies shows that fuzzy logic-based approaches exhibit remarkable performance in arrhythmia classification, with accuracy rates ranging from 88.88% to 99.88%. In particular, ANFIS proved to be particularly effective, consistently achieving near-perfect accuracy (approximately 99%) across multiple studies (S01, S02, S03, S05, S09, S12, S13, S14, S15). This performance is particularly significant when compared to traditional machine learning and deep learning methods, as illustrated in (Fig. 6), where certain studies compare the effectiveness of their fuzzy models with other established methods.

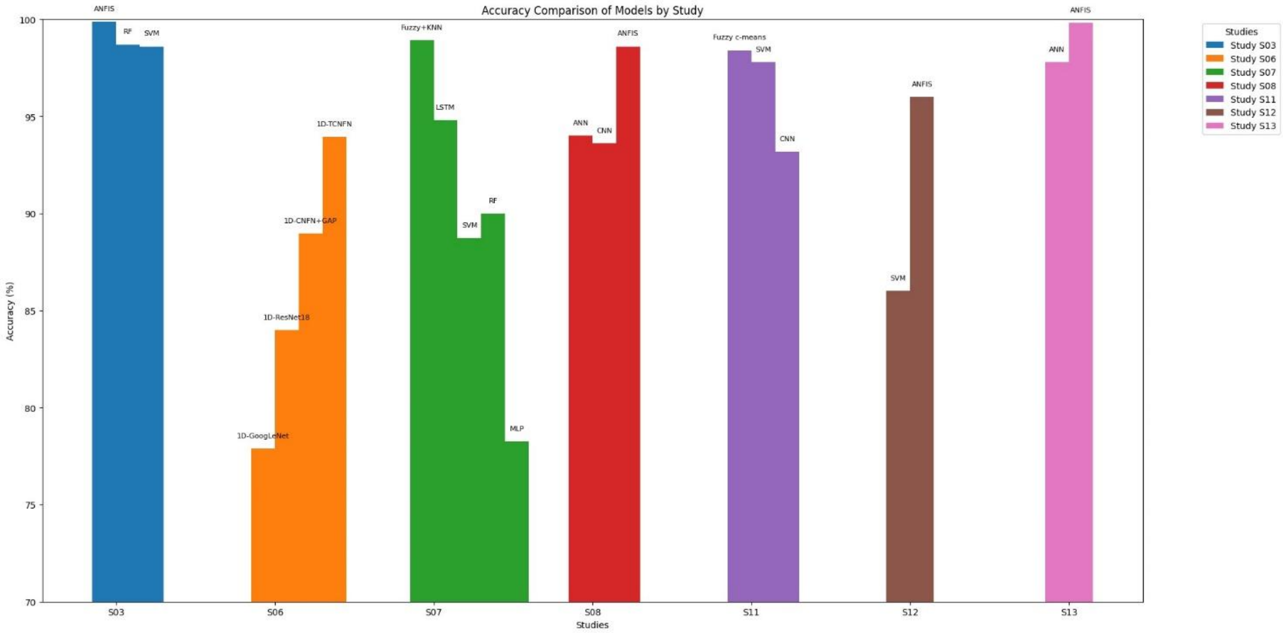

Fig. 6. Accuracy comparison of different machine learning models by study

The reliability of fuzzy logic systems is demonstrated by their consistent performance across studies using standard benchmark datasets, primarily the MIT-BIH Arrhythmia Database. This consistency in dataset usage facilitates meaningful cross-study comparisons while highlighting the robustness of fuzzy approaches in maintaining high classification accuracy.

Furthermore, hybrid approaches integrate fuzzy logic with other computational paradigms, demonstrating enhanced classification capabilities. In particular, studies S06 and S08 demonstrated how combining fuzzy systems with complementary methods optimizes classification performance. This suggests that fuzzy logic's inherent ability to handle uncertainty and imprecision effectively complements other algorithmic approaches.

A notable aspect is the explainability factor, where IFL was explicitly used to maintain interpretability while achieving competitive classification accuracy. This addresses a critical requirement in medical diagnostic systems where performance and decision transparency are essential. We highlight advances in IFL (S16, S17), which, since its introduction in 1986, has extended classical fuzzy logic by incorporating degrees of non-membership and hesitation. These additional parameters allow for more effective modeling of uncertainty and human-like hesitation in decision-making systems (Atanassov, 1986; Iancu et al., 2013).

5.2. Effectiveness of hybrid and multi-classifier systems (Q2 & Q3)

The reviewed studies highlight the effectiveness of combining fuzzy logic with other computational techniques, resulting in hybrid and multi-classifier systems that demonstrate improved arrhythmia classification performance, as shown in (Fig. 7). This synergistic approach leverages the unique strengths of fuzzy logic to handle uncertainty and imprecision, and complements other methods to create more robust and adaptive classification models.

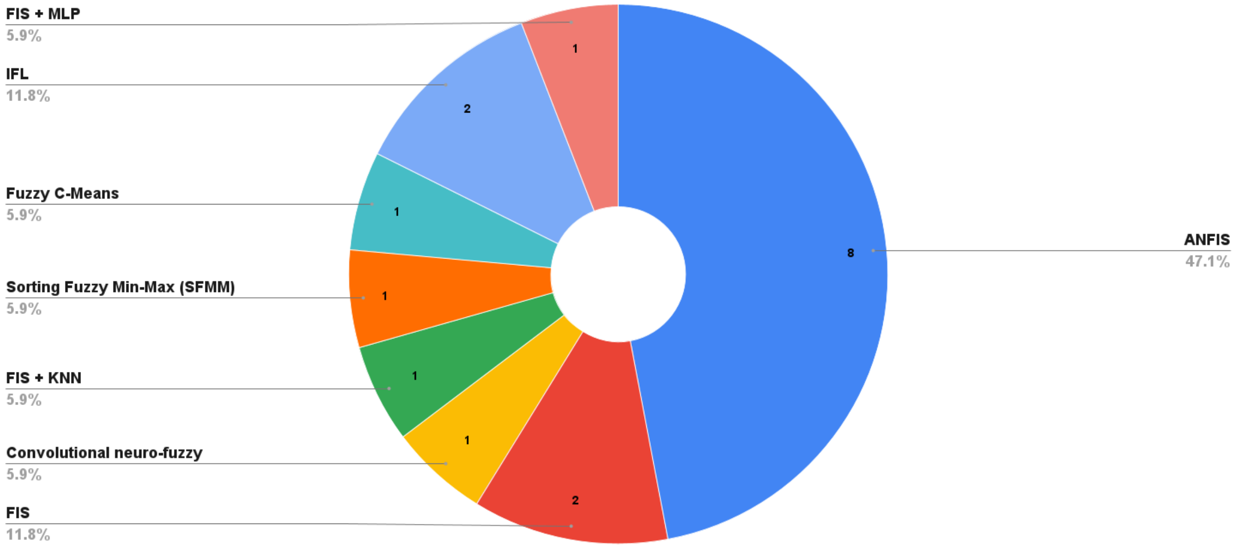

Fig. 7. Distribution of fuzzy logic-based models used in the studies

A prominent example of this hybridization is ANFIS, which integrates the structure of ANNs with the theoretical foundations of fuzzy logic. ANFIS-based models emerged as the dominant approach in the reviewed studies. This performance surpasses that of traditional FIS, which focuses on maintaining interpretability and transparency in decision making, as exemplified in study S07.

In addition, the integration of fuzzy logic with bio-inspired optimization methods and other computational paradigms significantly advances arrhythmia classification systems. This synergy leverages the uncertainty-handling capabilities of fuzzy logic with the robust optimization capabilities of evolutionary algorithms and swarm intelligence techniques. For example, study S12 used a novel approach that combined ANFIS with the Grasshopper optimization algorithm for VA classification, achieving impressive results of 96% accuracy. The role of the Grasshopper algorithm in optimizing the parameters of the fuzzy system improved the performance in detecting complex VA patterns.

These hybrid and multi-classifier systems demonstrate the power of combining fuzzy logic with complementary computational approaches (Ahmadi et al., 2018). By integrating the strengths of different techniques, researchers have developed more effective and adaptable arrhythmia classification models that outperform traditional stand-alone methods. For example, study S08 used a feature selection FIS fusion method to rank features obtained from different heuristic feature selection algorithms. This ability to handle many classes is particularly noteworthy, as many arrhythmia classification systems struggle to maintain high performance when faced with complex, multi-class problems. Similarly, study S06 examined the classification of 17 arrhythmia types using a hybrid fuzzy neural network approach, reporting an accuracy of 93.95%. This highlights the scalability of fuzzy logic-based systems in dealing with highly granular arrhythmia detection where traditional machine learning methods may fail. In addition, the reviewed studies demonstrate the effectiveness of fuzzy logic in addressing specific arrhythmia types that present unique challenges. S10 focused on the detection of AFib or LBBB in S05, two complex arrhythmias that are notoriously difficult to classify. By integrating fuzzy logic with wavelet analysis, as shown in S15, the researchers achieved high performance, underscoring the adaptability of fuzzy systems to handle complex arrhythmia patterns. Similarly, studies S12 and S11 addressed the classification of VAs, a critical task in cardiac monitoring, using a hybrid ANFIS-Grasshopper optimization algorithm approach and FCM clustering. The resulting system showed exceptional performance, highlighting the potential of fuzzy logic-based methods in micro-arrhythmia detection. More specific cases, such as fetal arrhythmias in S02, pose critical challenges to cardiologists due to uncertainties in ECG signal classification. This research highlights the value of interdisciplinary collaboration and the potential for advancements in arrhythmia classification. By combining fuzzy logic with complementary computational paradigms, researchers have developed highly effective and adaptable models to tackle complex, multi-class problems and address specific arrhythmia types with remarkable accuracy (Ansari et al., 2023).

The power of fuzzy logic in multi-classification scenarios is further exemplified in studies like S10, which introduced a Taguchi-based convolutional neuro-fuzzy network. This sophisticated hybrid approach successfully classified 17 different arrhythmia types with an accuracy of 93.95%. The fuzzy component in this system played a crucial role in managing the uncertainties inherent in discriminating between multiple arrhythmia classes, while the convolutional aspect improved feature extraction from ECG signals. The role of fuzzy logic as an optimizer is also evident in several studies. For example, S08 used a K-means clustering optimized fuzzy logic control algorithm that achieved 91.5% accuracy in classifying multiple arrhythmia groups. Here, fuzzy logic contributed to the classification process and optimized the clustering algorithm, resulting in more effective feature space partitioning and improved overall performance.

The power of fuzzy logic in hybrid multi-classification solutions is demonstrated in study S18, which presents a highly structured hybrid model for cardiac arrhythmia classification based on multiple classifiers and fuzzy logic integration, demonstrating the significant potential of such architectures to improve diagnostic performance. The hybrid model combines three different classifiers per lead - Fuzzy KNN, MLP - into two basic module units, each responsible for a separate ECG lead (MLII and V1/V2/V3). The outputs of these classifiers are fused using both Type1 FIS and Interval Type-2 FIS. The multi-classifier fusion approach is shown to be highly effective and accurate across 10 different arrhythmia classes.

These hybrid approaches address some of the key challenges in arrhythmia detection, such as dealing with noisy ECG signals (Menaceur et al., 2024) adapt to patient-specific variations, and manage the complexity of multi-class classification. By combining fuzzy logic with bio-inspired optimization methods, researchers have created more robust and flexible systems capable of dealing with the complex nature of cardiac arrhythmias (Gupta et al., 2024).

In addition, these hybrid models often show improved generalization capabilities. Combining the ability of Sfuzzy logic to handle imprecise data with the global optimization capabilities of bio-inspired algorithms results in models that can better adapt to new, unseen ECG patterns. This is particularly important in clinical settings, where the system may encounter arrhythmia patterns that differ from those in the training data (Vásquez-Iturralde et al., 2024).

5.3. Interpretability and explainability in clinical context (Q4)

The interpretability and explainability of AI models are critical factors in their adoption in the medical field, especially in critical areas such as arrhythmia detection (Cao et al., 2024). Fuzzy logic techniques offer a unique advantage in this regard by providing a reasoning framework that closely mimics human decision-making processes.

The inherent strength of fuzzy logic lies in its ability to improve the accountability of decision support systems through transparent decision flows and predictive processes (Cao et al., 2024). While most of the reviewed studies prioritized model accuracy and precision, leading to the adoption of ANFIS, fuzzy logic applications go beyond mere classification performance.

A significant finding from our analysis reveals two different approaches in applying fuzzy logic to arrhythmia classification. The first approach, represented by the majority of studies, focuses on achieving high classification accuracy through ANFIS and hybrid methods. However, the second approach, exemplified by studies S04 and S07, demonstrates the unique capability of fuzzy logic in risk assessment and clinical decision support. These studies effectively leverage the interpretability of fuzzy systems, particularly in IoT applications and risk assessment scenarios, proving particularly valuable in preventing fatal cardiovascular disease through early arrhythmia detection.

In addition, the practical implementation aspects of fuzzy logic systems provide additional advantages in resource-constrained environments. In particular, studies S10 and S02 demonstrate the feasibility of deploying hybrid fuzzy systems as embedded solutions, with S10 highlighting a critical advantage for real-world applications by using only ECG data from a single lead sensor deployed in a microcontroller and providing a local monitoring system with an LCD screen. The fundamental nature of fuzzy logic, based on IF-THEN rules, facilitates the development of lightweight models that can operate effectively within the hardware limitations of IoT devices, as shown in study S07, which uses fuzzy logic to focus on explainability through a feed system of ECG andSPO2sensors, providing a smartphone interface to interact with the classification output and make it interpretable. This characteristic makes fuzzy logic particularly suitable for edge computing applications in cardiac monitoring systems, where computational efficiency and reliable performance are essential.

The IFL's accuracy and ease of understanding make it a unique tool for complex medical applications such as arrhythmia classification and MDSS. Studies S16 and S17 show that IFL-based classifiers outperform traditional fuzzy systems when dealing with incomplete or noisy ECG data, increasing clinician confidence through standardized uncertainty representation. Hybrid AI architectures such as IFC-DNNs balance accuracy and interpretability.

The dual ability of fuzzy logic systems to maintain high classification accuracy while providing interpretable decision support positions them as valuable tools in clinical settings. (Mendel & Bonissone, 2021). This is especially true in scenarios where resource constraints and the need for accountable decisions intersect, such as in wearable cardiac monitoring devices or IoT-based healthcare systems.

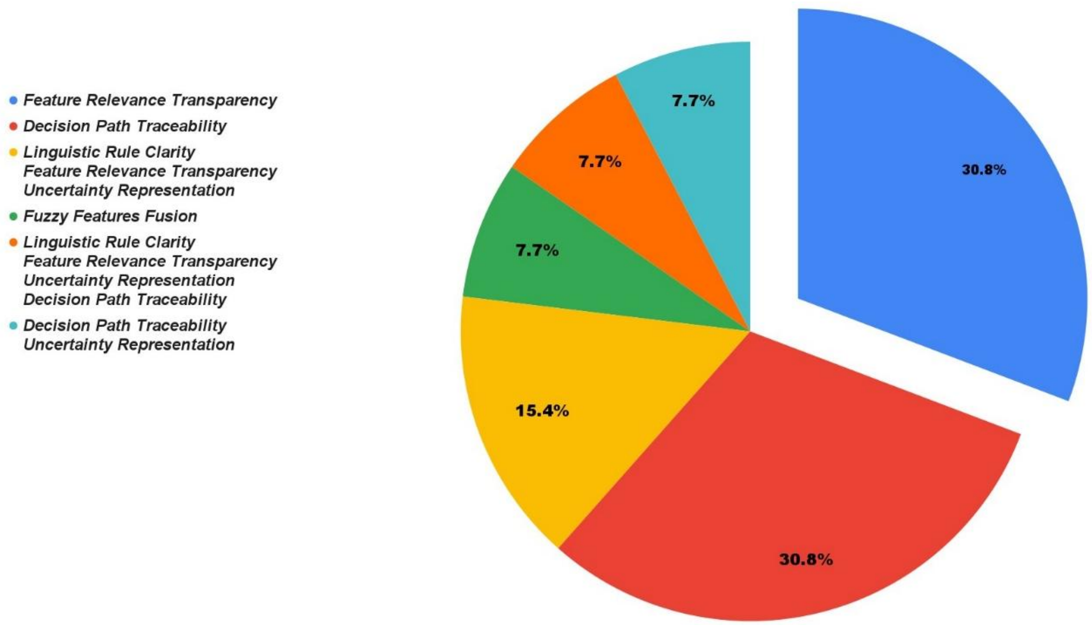

Fig. 8. Criteria used to evaluate fuzzy logic interpretability in studies

As shown in Figure 8, the dominance of Feature Relevance Transparency (30.8%) and Decision Path Traceability (30.8%) in the reviewed studies reflects the critical requirements in medical diagnostic systems. Feature Relevance Transparency is critical for model explainability, as it allows clinicians to understand which ECG features significantly influence arrhythmia classification decisions. Similarly, the equal emphasis on Decision Path Traceability demonstrates the researchers' focus on model interpretability, allowing healthcare professionals to follow the logical progression of how the system arrives at its diagnostic conclusions, a critical aspect for clinical confidence and adoption. The lower representation of other measures suggests that while aspects such as Linguistic Rule Clarity (15.4%) contribute to overall system comprehension, the primary concern in arrhythmia classification remains the ability to justify and trace diagnostic decisions in a clinically meaningful way.

6. CHALLENGES AND LIMITATIONS

The reviewed literature has several notable limitations that highlight opportunities for future research in the application of fuzzy logic to arrhythmia classification.

First, the predominant focus has been on the classification phase, while the potential of fuzzy logic to improve other aspects of the arrhythmia detection workflow remains underexplored. For example, study S08 demonstrated the effectiveness of fuzzy logic in data fusion, suggesting that researchers should investigate the integration of fuzzy techniques throughout the system pipeline beyond the classification task.

Moreover, while these studies heavily emphasize the superior accuracy of ANFIS-based models, the core principles of fuzzy logic, namely explainability and interpretability, deserve more attention. The reviewed literature suggests that researchers should shift their focus to capitalizing on the inherent eXplainable AI (XAI) capabilities of fuzzy systems, as exemplified in study S07, rather than solely optimizing for classification performance.

In addition, most studies rely on standard benchmark datasets such as the MIT-BIH Arrhythmia Database (Moody & Mark, 1992) and PTB Diagnostics ECG (Bousseljot et al., 2004) with only study S04 validating the proposed models using real-world clinical data. This discrepancy between laboratory settings and practical clinical implementation is a significant limitation. Future research must prioritize the evaluation of fuzzy logic-based arrhythmia detection systems using diverse, representative, and clinically validated data sets to ensure their robustness and suitability for real-world use.

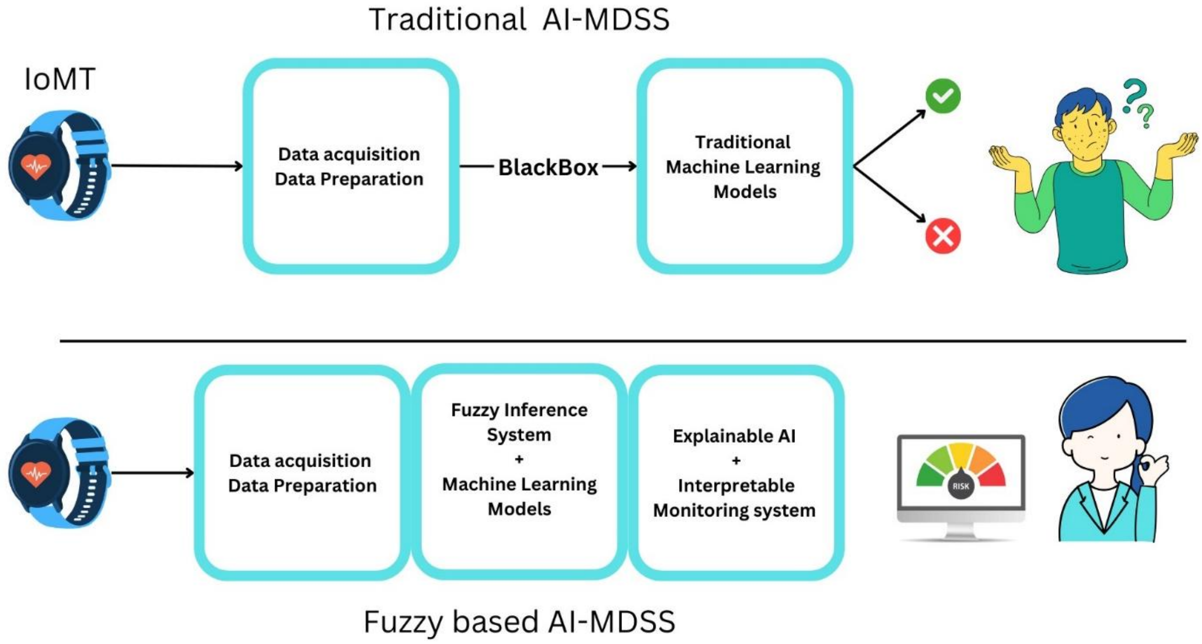

Fig. 9. Traditional AI-based vs. fuzzy-based medical decision support systems

Finally, the literature reviewed lacks a comprehensive exploration of the deployment and monitoring aspects of fuzzy logic-based systems. While the inherent lightweight structure of fuzzy models suggests their potential for edge computing and IoMT applications (Xing et al., 2024). However, only a few studies (S10, S06) have investigated these practical implementation considerations. As summarized in (Fig. 9), addressing the challenges associated with end-to-end system deployment and monitoring, especially in resource-constrained environments, should be a major focus of future research.

By addressing these limitations, future studies can leverage the unique strengths of fuzzy logic, such as its interpretability and multi-objective optimization capabilities, to develop comprehensive, clinically validated and deployable arrhythmia detection systems that can significantly improve patient care and clinical decision-making.

7. RESEARCH RECOMMENDATIONS

To advance the development of interpretable and clinically robust MDSS, we propose the following research directions based on the findings of this review and in line with recent methodological trends:

– Integrate real-world data validation: Future studies should prioritize the use of real-world clinical data for both training and validation. Validation on authentic, heterogeneous datasets is essential to assess model generalizability and avoid overfitting. Emphasis should be placed on data veracity to ensure that input signals reflect real clinical environments.
– Improve Explainability through Fuzzy Feature Sets: Incorporating fuzzy set theory into the feature extraction or transformation phase can significantly improve model transparency. Fuzzy representations (e.g., linguistic categories such as "high risk," "moderate rhythm variability") are more closely aligned with clinical reasoning and support better human-AI interpretability (Badhon et al., 2025).
– Embedding Fuzzy Logic into Classifiers: Embedding fuzzy inference mechanisms into classification architectures such as IFC or Adaptive ANFIS can enable joint reasoning over uncertain or imprecise data. These hybrid methods provide a bridge between data-driven learning and rule-based decision logic, enhancing both model performance and interpretability (Basu & Chaudhury, 2025).
– Hybrid Fuzzy-Deep Learning Models: Combining fuzzy logic with deep learning (e.g., CNNs, LSTMs) provides a powerful paradigm for capturing both low-level signal patterns and high-level semantic rules.

Research should explore hybrid architectures in which fuzzy systems support decision-level refinement or post-processing to help clinicians interpret complex model output with greater clarity.

- Use of fuzzy MDSS for real-time monitoring and visualization: We advocate application-oriented research that uses fuzzy logic to generate human-readable risk scores, trend alerts, or prognostic explanations. Such systems should facilitate data visualization through fuzzy language summaries to help both healthcare professionals and patients understand health status and risk over time.
- Establish transparent and trusted frameworks: To facilitate clinical adoption, it is imperative to develop end-to-end frameworks that prioritize transparency, explainability, and verifiability (Goktas & Grzybowski, 2025).

By adhering to these principles, future MDSS systems will not only achieve high performance, but also provide trustworthy, interpretable, and clinically actionable results. This is critical for supporting decision-making in high-stakes healthcare contexts and improving communication between healthcare professionals and patients.

8. CONCLUSIONS

This systematic literature review examines the application of fuzzy logic in arrhythmia detection through a comprehensive analysis of 18 peer-reviewed studies published between 2019 and 2024, following the PRISMA methodology. The review addressed four fundamental research questions: accuracy and reliability, effectiveness of hybrid systems, challenges of multiple classifiers, and implications for interpretability in clinical settings.

The results show that fuzzy logic-based approaches achieve remarkable classification accuracy (88.88% to 99.88%), with ANFIS-based hybrid models consistently showing superior performance. The integration of fuzzy logic with other computational intelligence paradigms, particularly in multi-classifier architectures, has proven effective in handling complex arrhythmia patterns and improving overall system robustness.

This review contributes significantly by identifying the dual advantage of fuzzy logic in providing high classification accuracy and improved model interpretability. The inherent ability of fuzzy systems to handle uncertainty while maintaining transparent decision-making processes positions them as valuable tools for explicable AI in clinical applications. This characteristic is particularly important in healthcare settings, where accurate diagnosis and clear justification of decisions are essential.

Despite these promising results, the review highlights critical challenges that need to be addressed. First, the reliance on benchmark datasets such as MIT-BIH limits the generalizability of the results. The lack of validation on diverse, real-world clinical data limits the applicability of these methods in practice. Second, while fuzzy logic inherently supports interpretability, most studies prioritize accuracy over explainability. This oversight undermines the clinical trust and usability of such systems, particularly in critical healthcare environments where decision transparency is paramount. Third, despite the lightweight nature of fuzzy logic models, the deployment and monitoring of fuzzy logic-based MDSS in resource-constrained environments remains underexplored.

This review highlights the transformative potential of fuzzy logic in MDSS, bridging the gap between high-performance arrhythmia classification and clinical interpretability. By addressing the highlighted challenges and leveraging its unique strengths, fuzzy logic can significantly advance the development of next-generation AI-driven healthcare systems, ensuring diagnostic accuracy and meaningful decision support in cardiac care. In addition, successful implementation in practice will require addressing regulatory standards, ensuring clinical workflow integration, and fostering trust among medical professionals. These factors are critical to the broader adoption and acceptance of AI-driven decision support tools in healthcare environments.

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Conflicts of interest

The authors declare no conflict of interest

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