Evolution of fuzzy logic in medical applications: methods, trends and clinical applications

Expert Systems With Applications 321 (2026) 132344

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Review

Evolution of fuzzy logic in medical applications: methods, trends and clinical applications

Massimo Salvi [a,*], Sengul Dogan [b], Mahesh Anil Inamdar [c,*], U. Raghavendra [c], Anjan Gudigar [c], Francesco Nitti [a], Andrea Ferraris [a], Turker Tuncer [b], Prabal Datta Barua [d], Filippo Molinari [a], U. Rajendra Acharya [e,f]

[a] Biolab, PolitoBIOMed Laboratory, Department of Electronics and Telecommunications, Politecnico di Torino, 10129 Turin, Italy
[b] Department of Digital Forensics Engineering, Technology Faculty, Firat University, Elazig, Turkey
[c] Department of Mechatronics, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, India
[d] School of Business (Information System), University of Southern Queensland, Australia
[e] Centre for Health Research, University of Southern Queensland, Australia
[f] School of Mathematics, Physics and Computing, University of Southern Queensland, Springfield, Australia

ARTICLE INFO

Keywords:
Fuzzy
Bio-medical
Machine learning
Healthcare
Deep learning
Image processing
Imaging modalities

ABSTRACT

Background: Fuzzy logic techniques have gained significant prominence in healthcare, primarily due to their ability to address and manage the inherent imprecision and uncertainty in healthcare data analysis. We conducted a comprehensive review investigating how fuzzy techniques have developed and been applied in healthcare between 2017 and 2025.
Methods: We conducted a systematic literature review following PRISMA guidelines, analyzing 91 papers from major medical and engineering databases. Our analysis focused on three distinct methodological streams: classical fuzzy systems, combined fuzzy-machine learning approaches, and emerging fuzzy-enhanced deep learning frameworks. We evaluated each paper's methodology, implementation details, and clinical relevance.
Results: The distribution of research approaches showed a balanced landscape across methodologies, with traditional fuzzy systems comprising 30.1%, hybrid approaches 34.4%, and fuzzy-deep learning implementations 33.3% of studies. Medical imaging dominated the application domains, led by MRI studies (36.3%) and CT applications (12.1%). Biosignal analysis also showed strong representation, particularly in EEG (22%) and ECG (7.7%) applications. Performance analysis revealed that both deep learning and conventional feature engineering methods achieved comparable accuracy rates of approximately 96.5%, with some variations in consistency across different applications.
Conclusions: This research area has undergone significant evolution, particularly since 2023, with an increased emphasis on incorporating fuzzy techniques into deep learning frameworks. This transition shows that fuzzy approaches, originally designed as standalone solutions, are now becoming critical components of modern healthcare AI systems, providing unique benefits in dealing with medical data uncertainty.

1. Introduction

Healthcare systems worldwide face increasing challenges in managing and analyzing complex medical data for accurate diagnosis and treatment decisions. Fuzzy logic is a mathematical method that deals with reasoning that is approximate rather than exact (Zadeh, 1992), (Zadeh, 2008), (Chatterjee et al., 2022). While Boolean logic operates in a binary fashion, permitting only true or false states, fuzzy logic embraces a spectrum of states lying between true and false. This inherent flexibility positions fuzzy logic as the method of choice for addressing problems characterized by vagueness or uncertainty (Zadeh, 1983), (Saha et al., 2022). Fig. 1 illustrates the numerous advantages associated with employing fuzzy logic in various systems (Fernández et al., 2015), (Ishibuchi, 2007). These advantages, including the ability to handle

* Corresponding authors.
E-mail addresses: massimo.salvi@polito.it (M. Salvi), sdogan@firat.edu.tr (S. Dogan), mahesh.inamdar@manipal.edu (M.A. Inamdar), raghavendra.u@manipal.edu (U. Raghavendra), anjan.gudigar@manipal.edu (A. Gudigar), francesco.nitti@polito.it (F. Nitti), turkertuncer@firat.edu.tr (T. Tuncer), Prabal.Barua@usq.edu.au (P.D. Barua), filippo.molinari@polito.it (F. Molinari), Rajendra.Acharya@usq.edu.au (U.R. Acharya).

https://doi.org/10.1016/j.eswa.2026.132344
Received 6 November 2025; Received in revised form 19 February 2026; Accepted 2 April 2026
Available online 3 April 2026

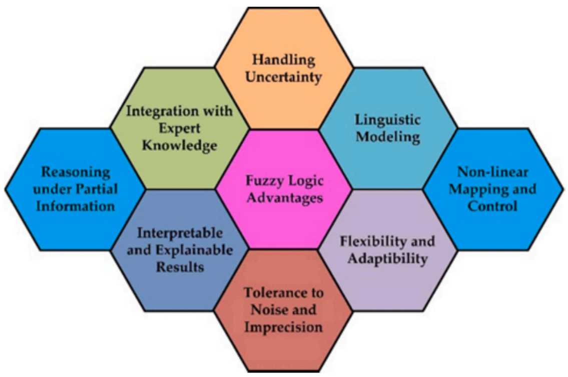

Fig. 1. The advantages of systems using fuzzy logic.

uncertainty, support natural language processing, and enable flexible reasoning, make fuzzy logic particularly suitable for healthcare applications where precision and interpretability are both crucial.

1.1. Background and context

Fuzzy techniques are firmly rooted in the concept of fuzzy sets, providing a robust framework for handling uncertain or imprecise information (Hong & Choi, 2000). In contrast to traditional binary sets, where elements are either in or out of a set, fuzzy sets introduce the concept of degrees of membership. These degrees, represented by values between 0 and 1, quantify the extent to which an element belongs to a particular set, accommodating partial membership.

Fuzzy logic finds its most valuable applications in systems dealing with imprecise or ambiguous data (Tavana & Hajipour, 2019). It excels at managing incomplete or subjective information by incorporating linguistic variables and fuzzy rules. Fuzzy systems leverage these rules and inference mechanisms to process inputs, make decisions, and produce outputs (Pedrycz & Gomide, 1998).

In healthcare applications, fuzzy logic techniques have proven valuable across multiple domains:

- *Medical Imaging Analysis*: Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), mammography analysis, processing, image segmentation and classification)
- *Biosignal Processing*: Electroencephalogram (EEG) signal analysis for neurological conditions, Electrocardiogram (ECG) interpretation for cardiac diagnosis, Electromyography (EMG) signal processing for muscular assessment)
- *Clinical Decision Support* (patient symptom analysis, disease diagnosis, treatment planning)

1.2. Motivation and objectives

Despite its potential, the application of fuzzy logic in biomedical engineering has not yet reached its full maturity. Gaps remain in terms of methodological standardization, evaluation consistency, and integration with modern AI pipelines. This review aims to address the following key research questions:

1. How effectively do fuzzy-based models address the complexities of biomedical image classification, segmentation, and signal/text models?
2. What are the prospects of fuzzy-based models within the domain of biomedical signals?
3. What are the current gaps in fuzzy-related biomedical engineering research?
4. How can fuzzy logic be optimally applied in biomedical signal processing?

To address these questions, we have established the following objectives:

Provide a comprehensive analysis of fuzzy-based healthcare models and their effectiveness

Evaluate the integration of fuzzy techniques with modern machine learning approaches

Identify the strengths and limitations of current fuzzy-based healthcare applications

Propose future research directions for advancing fuzzy techniques in healthcare

The paper is structured as follows: Section 2 presents the review strategy and methodology. Section 3 discusses the role of fuzzy logic in healthcare, while Sections 4 reviews fuzzy-based classification and segmentation processes. Finally, Sections 5 and 6 provide an in-depth discussion, future research suggestions, and conclusions.

2. Methods

2.1. Search strategy

We structured our review according to PRISMA guidelines (Tugwell & Tovey, 2021), establishing a systematic framework to examine research published between 2017 and 2025. Our literature search strategy centered on healthcare applications of fuzzy logic techniques. To ensure comprehensive coverage, we developed a search protocol combining key terms, including “fuzzy,” “health,” “diagnosis,” and “disease” in various combinations. The search, completed in July 2025, covered major scientific databases: PubMed for its medical focus, Scopus and IEEE Xplore for their technical depth, and Google Scholar for its broad academic coverage. This multi-database approach helped ensure we captured relevant work from both medical and technical perspectives. The complete search strings and data extraction protocol are detailed in Appendix A.

2.2. Selection process

The article selection process followed a systematic three-stage filtering approach, as illustrated in Fig. 2. Starting with a pool of 657 articles, we deleted 259 duplicate papers, yielding 398 unique titles. The second filtering stage removed 265 papers that were either non-English, irrelevant, or unrelated to healthcare applications, lowering the total amount to 133 articles. These initial screening steps were performed by one researcher (M.A.I.) based on objective criteria.

The final eligibility assessment was independently conducted by two researchers (M.A.I and M.S.) following the criteria detailed in Appendix B. Papers selected by both researchers were automatically included, while those rejected by both were excluded. For papers where there was disagreement, the researchers discussed each case until reaching a consensus.

Our paper selection process prioritized research published in established journals that demonstrated practical clinical value. We required strong empirical evidence and thorough methodological documentation for inclusion. Each paper underwent careful evaluation of its scientific merit, with particular attention to the clarity of fuzzy logic implementations and validation procedures. Studies lacking robust validation or clear healthcare applications were not included. This process led to a final selection of 88 unique papers that formed the core of our analysis. More details about the study quality assessment are reported in Appendix B.

From the selected works, we extracted key information covering research objectives, methodological approaches, healthcare applications, and performance results. We organized this data systematically, documenting details from all 88 papers in comprehensive Appendix tables. We paid special attention to innovative applications and

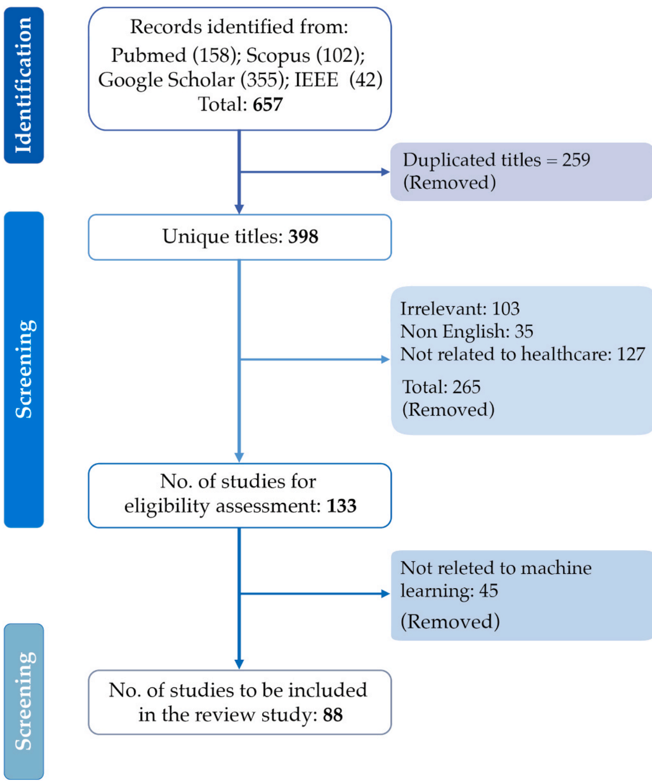

Fig. 2. PRISMA guidelines used during the review.

successful integration with other computational methods, particularly noting how fuzzy techniques complemented existing healthcare solutions.

2.3. Types of data covered in this review

In healthcare applications, two main categories of data emerge as primary targets for fuzzy-based analysis: medical imaging and biosignals.

Medical imaging encompasses various modalities, each providing distinct information about the structure and function of the human body. MRI employs powerful magnetic fields and radio waves to produce detailed visualizations of internal structures without the use of ionizing radiation (Katti et al., 2011). This imaging modality excels in delivering high-resolution images of soft tissues (including the brain, spinal cord, muscles, and blood vessels) and is a widely used imaging modality for diagnosing neurological disorders, musculoskeletal injuries, and cardiovascular conditions (Schenck, 1996). On the other hand, CT combines X-rays with computational methods to generate detailed cross-sectional images. Our review shows significant applications in lung nodule detection, COVID-19 diagnosis, and cancer detection. CT scans offer greater detail and precision compared to conventional X-ray imaging, making them especially valuable for diagnostic purposes (Sera, 2021).

Other imaging modalities covered in our review include retinal imaging, dental X-rays, mammography, and ultrasound applications. These modalities have shown particular effectiveness in specific diagnostic tasks such as retinal vessel segmentation, dental disease detection, breast cancer classification, and cardiac abnormality detection (Freudenberger et al., 2001).

In the realm of biosignals, two main types dominate healthcare applications:

- EEG records the brain's electrical activity via scalp sensors. Our review highlights its extensive use in epilepsy detection (Rabcan et al., 2022), Alzheimer's disease diagnosis (Cataldo et al., 2024), emotion recognition (Dhara et al., 2024), and depth of anesthesia monitoring.
- ECG monitors the heart's electrical activity. The reviewed studies demonstrate its crucial role in arrhythmia detection and cardiac abnormality classification (Muthuvel et al., 2019), (Abagaro et al., 2024).

2.4. Fuzzy techniques reviewed

Fuzzy techniques have found a natural synergy with both machine learning (ML) and deep learning (DL) paradigms. In the ML-based context, fuzzy logic is integrated with traditional machine learning algorithms to handle uncertainty and imprecision within data, enhancing model adaptability. Conversely, in the DL-based realm, fuzzy techniques are used to introduce interpretability and rule-based decision-making into deep neural networks. The basic machine learning techniques are given in Fig. 3.

In classical machine learning, the Adaptive Neuro Fuzzy Inference System (ANFIS) is a cornerstone technique that combines fuzzy logic and neural networks to construct a sophisticated inference system for handling uncertainty (Karaboga & Kaya, 2019). ANFIS uses a powerful hybrid learning technique that combines gradient descent optimization and least-squares estimation. Fuzzification transforms input variables into linguistic terms, fuzzy rules define relationships between inputs and outputs, fuzzy inference determines membership degrees, and defuzzification converts fuzzy results into precise values. The learning component continuously adapts system parameters to improve performance (Karaboga & Kaya, 2019), (Jang, 1993). Recent advances in this direction have led to Evolving Fuzzy Systems (EFS) that offer enhanced capabilities for online learning and real-time adaptation (Andonovski et al., 2026), (Škrjanc et al., 2019).

The field of traditional fuzzy-based machine learning extends beyond ANFIS to encompass several approaches. Fuzzy Clustering, particularly the Fuzzy C-Means algorithm, allows data points to belong to multiple clusters simultaneously, reflecting the natural ambiguity in medical data (Bataineh et al., 2011). Fuzzy Decision Trees incorporate uncertainty directly into the decision-making process, while Fuzzy Neural Networks merge the learning capabilities of neural networks with fuzzy logic's ability to handle imprecise information (Yuan & Shaw, 1995), (Buckley & Hayashi, 1994). Researchers have successfully integrated fuzzy logic into Support Vector Machines and Bayesian Networks, creating systems better equipped to process uncertain medical data (Lin and Wang, 2002), (Yazdi & Kabir, 2017).

This integration has been particularly useful in deep learning applications, where fuzzy approaches have improved neural network performance and interpretability. The combination has been particularly useful in medical picture classification, when fuzzy-enhanced convolutional networks and attention mechanisms outperformed traditional approaches. Particularly relevant is their role in improving the interpretability of deep learning models through fuzzy rule extraction, addressing one of the key challenges in medical AI applications (R. Das et al., 2021), (Deng et al., 2017).

2.5. The role of fuzzy in machine learning models in healthcare

Fuzzy theory offers various techniques that have been integrated into ML processes, complementing the techniques discussed in the previous section. ML approaches typically comprise four fundamental phases: feature extraction, feature selection, classification, and information fusion. While early fuzzy methods focused primarily on classification through if-then rules, contemporary approaches have evolved to incorporate fuzzy techniques across the entire ML pipeline (Ahmed et al., 2022), (Chen et al., 2015), as illustrated in Fig. 4.

Fuzzy-based techniques for feature extraction have been developed for healthcare applications. Recent research has demonstrated particularly encouraging results when fuzzy membership functions are used to

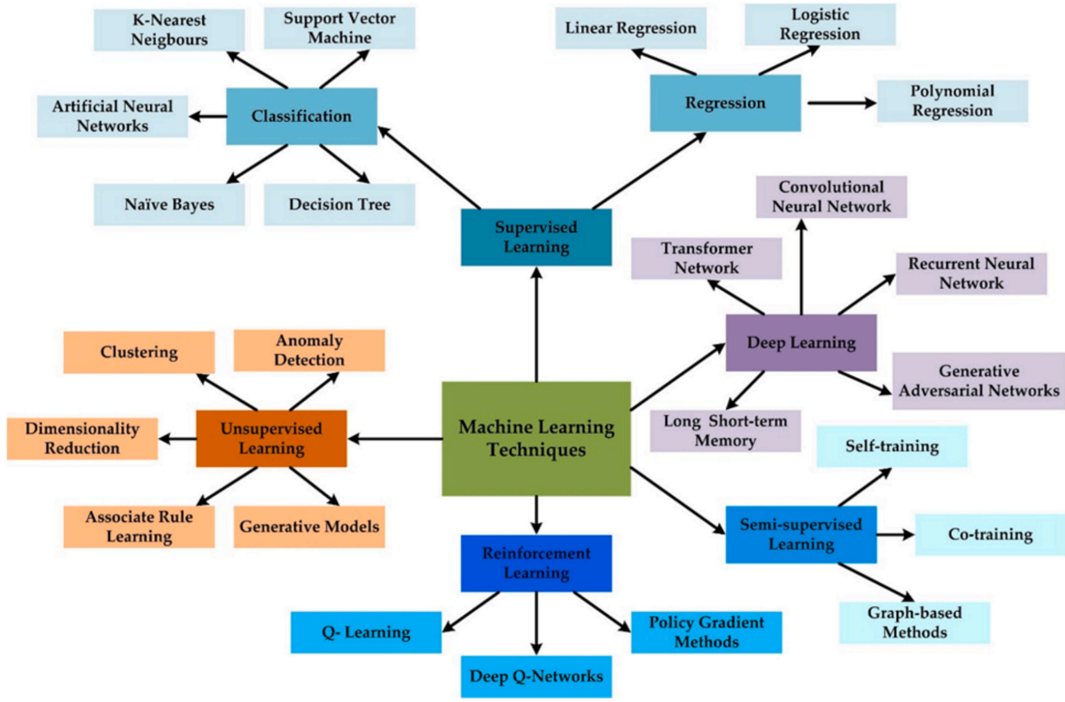

Fig. 3. A sample of basic machine learning techniques.

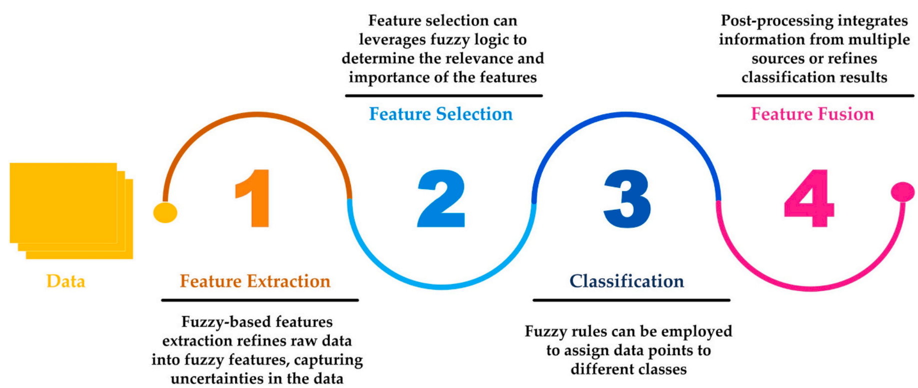

Fig. 4. Block depiction of the fuzzy decision-making models.

analyse how medical data connects to specific diagnostic categories (Ghasemi et al., 2020b). These methods complement fuzzy entropy measurements, which have proven useful in assessing uncertainty levels in complex medical datasets (Amezquita-Sanchez et al., 2021). Researchers have successfully used fuzzy clustering to discover trends in patient data (Alam et al., 2019), and fuzzy granulation to break down complex medical information into more digestible, clinically useful segments (Pedrycz & Sosnowski, 2000). More complex methods include rule-based systems that extract information via if-then linkages.

Fuzzy techniques to feature selection in high-dimensional data provide robust answers via a variety of mechanisms. These include relevance and redundancy metrics to evaluate feature importance (Sathiya & Sathiyabhama, 2019), rough sets to manage uncertainty, and mutual information techniques to quantify feature-target interactions (Hoque et al., 2016). Recent methods have also included genetic algorithms for optimization (G. T. Reddy et al., 2020) and multi-criteria decision-making approaches (Tzalavra et al., 2022).

Fuzzy logic techniques have greatly improved modern classification approaches in medical diagnostics. By integrating membership degrees into traditional classification methods, several works have developed more nuanced ways to handle the inherent uncertainty in medical data (Chowdhary et al., 2020). Recent research has concentrated on self-organized architectures that employ fuzzy logic for model selection (Zhou et al., 2024). These approaches enable adaptive and automated decision-making in complex healthcare scenarios.

3. Results

3.1. Overview of fuzzy applications in healthcare

Our analysis of research trends from 2017 to 2025 reveals a significant shift in how fuzzy techniques have been applied in healthcare, moving from traditional standalone systems to integrated approaches with modern AI techniques. As shown in Fig. 5, publication patterns reflect changing attitudes toward fuzzy logic in medical applications. The field saw steady growth through 2020, indicating increasing recognition of fuzzy logic's potential in healthcare. Then, we observed a temporary decline between 2021 and 2023 (from 15 papers in 2020 to 4 papers in 2023, representing a 73% reduction), coinciding with healthcare's widespread adoption of conventional DL approaches. The

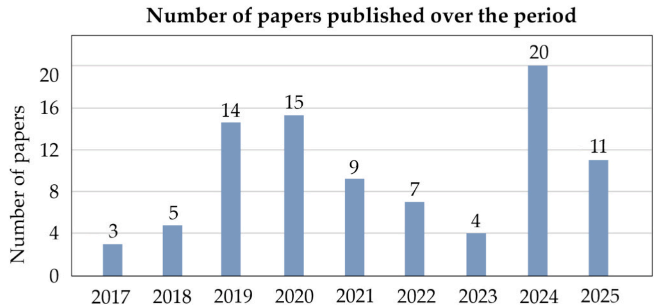

Fig. 5. Annual distribution of fuzzy-based healthcare publications (2017–2025).

situation transformed in 2024, resulting in a significant rebirth of fuzzy-based research. The comeback appears to be fueled by two major elements: the performance saturation of conventional DL in various healthcare tasks, and the growing recognition of fuzzy logic's capability to model uncertainty in biomedical data. This trend indicates a more sophisticated approach, with fuzzy approaches complementing rather than competing with deep learning models.

Initial research from 2017 to 2020 relied mainly on conventional fuzzy clustering and classification approaches, with studies typically reporting accuracy rates between 85% and 90% (Almotiri et al., 2018). In more recent research (2021–2025), where the integration of fuzzy methods with deep learning architectures has pushed accuracy rates consistently above 95% (Ding et al., 2023), (Lyu et al., 2025).

The integration of fuzzy techniques with different computational approaches has also evolved in recent years. Our data, shown in Fig. 6, reveals a clear predominance of hybrid approaches. While traditional fuzzy systems account for 18% of studies (16 papers), hybrid fuzzy-machine learning methods represent the majority with 55% (48 papers), and fuzzy-enhanced deep learning comprises the remaining 27%.

From a temporal point of view (Fig. 7), traditional fuzzy approaches maintained relatively low and stable publication rates throughout 2017–2025, with modest numbers each year. In contrast, hybrid fuzzy-ML methods showed clear dominance in 2019–2020, contributing to nearly all publications in those years. Fuzzy-enhanced deep learning approaches have shown a steady increase in recent years, reaching comparable levels to hybrid ML approaches in 2024 and surpassing them in 2025. The notable increase in fuzzy logic-enhanced deep learning, which now dominates recent research, accounts for almost half of all articles published from 2023 to 2025. This shift indicates a successful integration of fuzzy logic interpretability with the computational power of deep learning.

Our analysis reveals distinct patterns in how fuzzy techniques are being applied across different medical fields. Fig. 8 illustrates this distribution, showing medical imaging as the primary application area. MRI studies represent the largest segment at 35.3% of publications, followed by CT imaging at 12.5%. A variety of other imaging techniques (including retinal scans, ultrasound, X-rays, and microscopy) make up

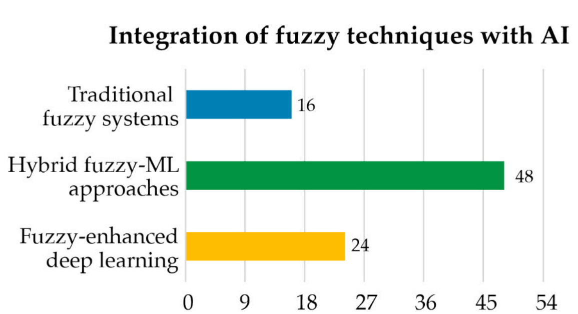

Fig. 6. Distribution of computational approaches in fuzzy-based healthcare applications.

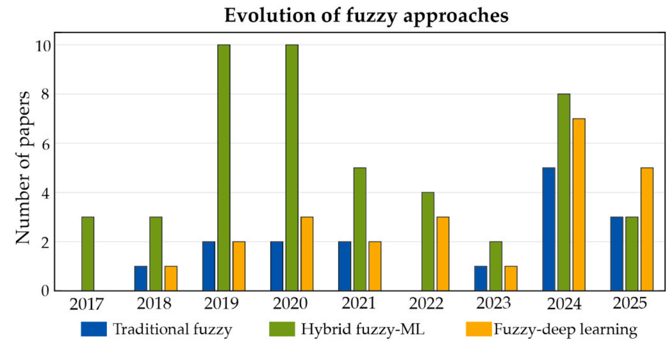

Fig. 7. Temporal distribution of fuzzy-based publications from 2017 to 2025, categorized by methodological approach: traditional fuzzy systems (blue), hybrid fuzzy-ML (green), and fuzzy-enhanced deep learning (yellow).

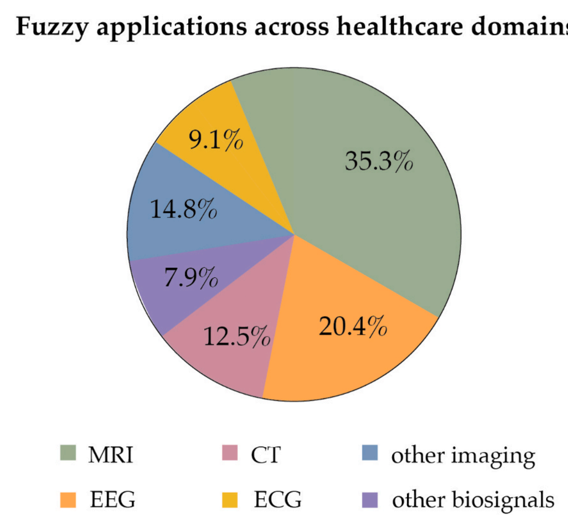

Fig. 8. Distribution of fuzzy applications across healthcare domains with detailed modality breakdown.

an additional 14.8% of the research. Beyond imaging, biosignal analysis emerged as another key application area. EEG research features prominently, accounting for 20.4% of publications and underscoring fuzzy logic's value in analyzing brain activity. Cardiac studies through ECG analysis comprise 9.1% of the work, while other biosignal applications (spanning EMG, heart sounds, blood volume measurements, and voice analysis) represent 7.9%.

These data reveal a strong presence of brain-related applications when combining MRI and EEG studies. This emphasis likely reflects the unique challenges of neurological data, where fuzzy techniques prove especially useful for managing the inherent variability and complexity of brain-related measurements.

3.2. Medical image analysis

Our systematic review reveals that fuzzy logic techniques have been extensively applied to medical image analysis, with particular emphasis on MRI and CT imaging. These applications show a clear evolution from traditional fuzzy approaches to sophisticated hybrid systems integrating deep learning architectures.

MRI-based applications represent a significant portion of fuzzy logic implementations in medical imaging (Table C1). Brain tumor detection and segmentation emerge as primary applications, with approaches demonstrating improved accuracy and reduced false positives compared to traditional methods (Zaman et al., 2025). Raja and Rani (Siva Raja & Rani, 2020) developing a Bayesian fuzzy clustering algorithm integrated with a deep autoencoder, reaching 98.50% accuracy. Alzheimer's disease detection represents another crucial application area. Togacar et al. (Toğaçar et al., 2021) combined fuzzy color image enhancement with hypercolumn techniques, achieving remarkable accuracy (99.94%). The evolution of these methods is evident in recent studies like Arpaia et al. (Arpaia et al., 2025), who utilized multiscale fuzzy entropy with amplitude preprocessing. Beyond these primary applications, fuzzy techniques have shown promise in other neurological conditions. Kaur et al. (Kaur et al., 2019) achieved 98% accuracy in Parkinson's disease detection using an innovative combination of the BAT algorithm and adaptive fuzzy K-nearest neighbor approach. The field has expanded to include successful applications in sarcoma classification (Hermessi et al., 2019) and cancer genome analysis (Özyurt et al., 2019).

In CT imaging specifically, researchers have made significant strides in three key areas: lung nodule detection, COVID-19 diagnosis, and cancer detection. The field evolved from Farahani's early work (Farahani et al., 2018), which achieved 93.40% accuracy using modified fuzzy c-means clustering, to more sophisticated approaches like Manickavasagam and Selvan's (Manickavasagam & Selvan, 2019) neuro-fuzzy classifier, which reached 97.79% accuracy. Fuzzy-based approaches have also been recorded for COVID-19 analysis using CT imaging. Kundu's team (Kundu et al., 2021) developed a fuzzy-based neural network achieving 98.93% accuracy, while Chharia et al. (Chharia et al., 2022) reported 97.47% accuracy with their conv-fuzzy network. Cancer detection has seen similar progress, from Das's work (A. Das et al., 2019) achieving 95.02% accuracy in liver cancer detection to Li's recent advancement (L. Li et al., 2024) in tumor imaging, achieving Dice coefficients of 0.85–0.86 in PET/CT analysis.

Recent trends in medical imaging clearly show how fuzzy techniques are being successfully combined with advanced ML methods. This evolution is particularly evident in radiology, where Ghasemi and colleagues (Ghasemi et al., 2020a) achieved remarkable results (99.38% accuracy) by developing a fuzzy discriminative sparse coding approach for MRI. Similarly, in CT imaging, Song's team (Song et al., 2022) demonstrated the power of integrated approaches through their innovative deep fuzzy model. Furthermore, recent developments have increasingly focused on multi-modal and transfer learning techniques, as demonstrated by Mahanty et al. (Mahanty et al., 2022)'s work, which achieved 99.15% accuracy using Sugeno fuzzy integral for COVID-19 detection, indicating a promising direction for future developments in medical image analysis.

3.2.1. Other imaging applications

Fuzzy techniques have been successfully applied across various other imaging modalities. In retinal imaging, Almotiri et al. (Almotiri et al., 2018) developed a morphological adaptive fuzzy thresholding approach, achieving accuracies ranging from 83.40% to 95.88% across multiple datasets. This work was complemented by Memari et al. (Memari et al., 2019), who combined fuzzy C-means clustering with matched filtering for retinal vessel segmentation. Breast cancer detection has improved significantly thanks to several imaging modalities. Chowdhary et al. (Chowdhary et al., 2020) used intuitionistic possibilistic fuzzy C-means clustering for mammography analysis and obtained 98.85% accuracy. Biesok et al. (Biesok et al., 2024) have presented a hybrid technique to ultrasound imaging that combines distance-adapted fuzzy connectedness with an autoencoder CNN, resulting in a Dice coefficient of 0.79.

Novel applications have emerged in specific fields. Wang et al. (W. Wang et al., 2025) created an expert knowledge-guided deep fuzzy network for predicting cervical lymph node metastasis in thyroid cancer, and Kavitha et al. (Kavitha et al., 2023) used ultrasound images to diagnose prenatal hypoplastic left heart syndrome using fuzzy techniques. Recent developments demonstrate an increasing integration of fuzzy approaches with advanced deep learning frameworks. This is exemplified by Jiao et al. (Jiao et al., 2025)'s BS-Mamba architecture for breast tumor segmentation in ultrasound images, and Ding et al. (Ding et al., 2023)'s work combining fuzzy techniques with transformer architectures across multiple imaging applications, achieving consistently high accuracies (96.60–97.78%).

3.3. Biosignal analysis

Our systematic review of biosignal analysis reveals extensive applications of fuzzy techniques in EEG and ECG signal processing, with additional specialized applications in other physiological signals.

EEG signal analysis has emerged as a primary application area, particularly in neurological conditions. Kocadagli and Langari (Kocadagli & Langari, 2017) developed a hybrid approach combining artificial neural networks with fuzzy relations, achieving 99.80% accuracy in epileptic seizure detection. Amezquita-Sanchez et al. (Amezquita-Sanchez et al., 2021) detected Alzheimer's disease using entropy and fuzzy logic systems, with an accuracy of 86.90%. Recent advances include unique applications in emotion recognition, where Dhara et al. (Dhara et al., 2024) obtained up to 99.38% accuracy utilizing a fuzzy ensemble-based deep learning approach. These developments in emotion recognition have also extended to real-time applications (Leite et al., 2021), demonstrating the practical potential of adaptive fuzzy approaches in dynamic monitoring scenarios. Shahbakhti et al. (Shahbakhti et al., 2024) made significant advances in the depth of anesthesia monitoring by combining fuzzy entropy with Gaussian and exponential membership functions.

Fuzzy approaches in ECG analysis have proven to be extremely effective at detecting heart abnormalities. Kumar et al. (Kumar et al., 2023) performed arrhythmia identification with 98.66% accuracy using coupled fuzzy clustering and deep neural networks. Lyu et al. (Lyu et al., 2025) developed a multimodal feature fusion strategy using a transformer-based architecture, attaining 98.46% accuracy and proving the successful integration of fuzzy approaches with recent deep learning architectures.

3.3.1. Other biosignal applications

In addition to EEG and ECG, novel uses for additional physiological signals have arisen. Vallejo et al. (Vallejo et al., 2018) used time–frequency analysis, fuzzy entropy, and neural networks to detect neuromuscular diseases with 98% accuracy. In the domain of heart sound analysis, several fuzzy-based approaches have been presented. Soares et al. (Soares et al., 2020) created a zero-order autonomous learning multiple-model with a neuro-fuzzy technique for heart sound classification, which achieved 93.04% accuracy. De Campos Souza et al. (De Campos Souza & Lughofer, 2020) developed an interpretable evolving fuzzy neural network showing robust performance in heart sound identification. More recently, Xiao et al. (F. Xiao et al., 2024) advanced this field by combining 1D + 2D CNN with evolving fuzzy systems, achieving 96–99% accuracy in cardiovascular disease diagnosis. Prabhakar et al. (Prabhakar et al., 2020) used fuzzy-based animal migration optimization to classify photoplethysmography signals with 95.05% accuracy.

Recently, Yu et al. (Yu et al., 2025) introduced refined fuzzy entropy techniques for analyzing stroke and aging effects on the neuromuscular system, while Azadi et al. (Azadi et al., 2021) achieved 95.32% accuracy using interval type-2 fuzzy sets for Parkinson's disease detection through voice analysis. These numerous applications highlight fuzzy methods' adaptability in processing and interpreting a wide range of physiological information.

3.4. Methodological approaches

Our systematic analysis reveals a clear evolution in fuzzy methodologies for healthcare applications, progressing from fundamental techniques to sophisticated hybrid systems and modern architectures. Traditional fuzzy approaches laid the foundation through fuzzy clustering and rule-based systems. Fuzzy C-means clustering has proven particularly effective in medical image segmentation, as demonstrated by Chowdhary et al. (Chowdhary et al., 2020) achieving 98.85% accuracy in mammography analysis. Rule-based fuzzy inference systems have excelled in diagnostic applications, whereas fuzzy entropy-based methods have proven to be extremely useful in biosignal analysis, as demonstrated by the study of Cataldo et al. (Cataldo et al., 2024) on Alzheimer's disease identification via EEG analysis.

The advancement of fuzzy methodologies resulted in the creation of hybrid approaches that combined fuzzy logic with alternative computational paradigms. Tzalavra et al. (Tzalavra et al., 2022) revealed that adaptive neuro-fuzzy inference systems (ANFIS) are a powerful tool for classifying breast tumors. Fuzzy-genetic algorithms have showed potential in optimization problems, whereas fuzzy-evolutionary computation improves adaptive capacities, as demonstrated by Mahanty et al. (Mahanty et al., 2022), who achieved 99.15% accuracy in COVID-19 identification.

Recent years have seen the advent of innovative architectures that integrate fuzzy techniques with state-of-the-art DL frameworks. Ding et al. (Ding et al., 2023) demonstrated that deep fuzzy networks performed very well in complex healthcare tasks, reaching high accuracy (>96%) across a variety of imaging applications. Fuzzy-enhanced transformers are a modern invention that incorporates fuzzy logic into attention processes. Novel architectures, such as BS-Mamba (Jiao et al., 2025), highlight the effectiveness of combining fuzzy approaches with new DL algorithms for image segmentation tasks.

The rise of deep learning models since the 2020s has led to a shift in how fuzzy techniques are applied, with an increasing focus on their role in enhancing deep learning architectures rather than serving as standalone solutions. This integration has proven particularly effective in handling the uncertainty and imprecision inherent in healthcare data while maintaining the high-performance characteristics of deep learning models.

3.5. Performance analysis

In this section, we focused on classification tasks as they represent the most common applications across the reviewed studies. We aggregated classification accuracy results across different medical domains into three methodological categories: traditional fuzzy systems, hybrid fuzzy-ML approaches, and fuzzy-enhanced deep learning methods. The result of this comparison is shown in Fig. 9. Traditional fuzzy systems (n = 12) showed a mean accuracy of 92.32% (±6.14%), demonstrating the baseline capability of fuzzy logic in medical classification tasks. Hybrid fuzzy-ML approaches (n = 26) achieved improved performance with 95.17% (±4.60%) mean accuracy, benefiting from the integration of machine learning techniques with fuzzy systems. Fuzzy-enhanced deep learning methods (n = 19) demonstrated the highest mean accuracy at 95.93% with notably lower variability (±2.86%), suggesting more robust and consistent performance. While these comparisons span different healthcare applications and dataset sizes, the trend indicates that both hybrid and deep learning integrations with fuzzy systems can enhance classification performance while maintaining interpretability.

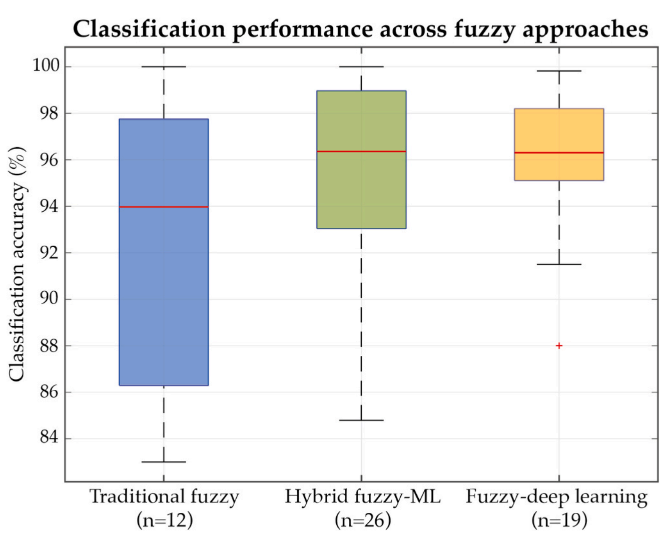

Fig. 9. Classification accuracy distribution across fuzzy approaches in medical applications. The boxplot shows the performance comparison between traditional fuzzy (n = 12), hybrid fuzzy-ML (n = 26), and fuzzy-deep learning (n = 19) methods.

To assess the statistical significance of these performance differences, we conducted both parametric (ANOVA) and non-parametric (Kruskal-Wallis) tests, followed by pairwise comparisons. Despite the observed trends in mean accuracy and variability, statistical analysis revealed no significant differences between the three approaches (all pairwise p-values > 0.05). This suggests that the choice of fuzzy methodology may be less influential on overall performance than other factors such as the specific medical domain, data characteristics, and task complexity. Nevertheless, the consistently lower variability observed in deep learning approaches (±2.86%) compared to traditional methods (±6.14%) points to more stable performance across different applications, even if this difference did not reach statistical significance.

We initially considered conducting a dataset-stratified performance analysis to examine whether specific benchmark datasets (e.g., BraTS, MIT-BIH) might influence reported accuracies. However, this approach proved methodologically problematic for several reasons. Even within the same dataset, studies addressed substantially different tasks. For example, BraTS studies included binary tumor detection (Siva Raja & Rani, 2020), (Narmatha et al., 2020), multi-class tumor type classification (Mayeta-Revilla et al., 2025), and pixel-level segmentation (Khosravanian et al., 2021), with different evaluation metrics (accuracy vs. Dice coefficient). Additionally, studies using identical datasets often employed fundamentally different preprocessing pipelines, validation strategies (k-fold vs. holdout, different train-test splits), and feature extraction methods, making aggregated comparisons potentially misleading. Finally, dataset-specific subgroups would have resulted in very small sample sizes (n < 5 in many cases), undermining the statistical power and reliability of any comparative analysis.

4. Discussion

4.1. Main findings

Our systematic review highlights that fuzzy logic serves as a flexible mathematical model adept at addressing challenges posed by uncertain situations. Early research demonstrated this through fundamental approaches (Alam et al., 2019) achieving 97.50% accuracy using template-based K-means and improved fuzzy C-means for brain tumor detection.

The investigation demonstrates the importance of fuzzy-based preprocessing techniques in healthcare applications. Notable examples include (K. R. Reddy & Dhuli, 2023), which combined spatial fuzzy c-means threshold with local binary pattern to achieve accuracies of up to 100% in brain tumor detection, and (Singh et al., 2024), which demonstrated the effectiveness of preprocessing with their local parameter-free fuzzy factor approach. Effective segmentation has proven critical for classification models, with widely used fuzzy segmentation methods such as neutrosophy and fuzzy C-means demonstrating significance.

Recent research shows an increasing convergence between fuzzy logic and deep learning approaches. Notable examples include a study using optimized deep neuro-fuzzy networks (Neelima et al., 2024) that achieved 91.50% accuracy in brain tumor classification. Similarly impressive results came from research on ECG analysis (X. Wang et al., 2025), where a multiscale deep neuro-fuzzy network achieved accuracies between 86.83% and 98.97%.

The rise of deep learning in the 2010 s initially led to decreased interest in purely fuzzy approaches, despite their proven classification accuracy. Transfer learning has helped address the challenge of limited datasets, though performance can vary significantly across different data types. Current trends show a shift toward ensemble models that combine deep learning with fuzzy techniques, particularly for post-processing to enhance the collective performance of multiple deep learning models. Researchers are also finding success using fuzzy-based segmentation alongside deep networks, especially in improving diagnostic accuracy, where attention mechanisms aren't employed.

4.2. Advantages of the fuzzy-based models for healthcare

The main technological advantages of fuzzy-based techniques are their adaptability to uncertain conditions and effectiveness in preprocessing tasks. These techniques have been particularly useful in biological signal processing and picture segmentation, as evidenced by (Hassan et al., 2019), which achieved 99.20% accuracy in brain segmentation using fuzzy intelligence and Gaussian mixture models. In signal processing, fuzzy-based feature extraction and classification algorithms use wavelet transformations to extract multilayer features, resulting in more comprehensive analysis and better comprehension of healthcare signals (Bhattacharyya et al., 2017). The use of *meta*-heuristic optimization techniques improves segmentation capabilities, notably in detecting anomalies such as nodules or tumors (Sathiya & Sathiyabhama, 2019). Furthermore, when paired with deep learning architectures, fuzzy techniques function as effective post-processing methods (Cai et al., 2021), boosting the diagnostic capabilities of non-attention-based models and overall classification performance.

In terms of clinical applications, fuzzy models provide interpretability, robustness, and dependability when dealing with unclear data. Their ability to handle subjective and imprecise data, such as patient symptoms or expert judgments, makes them ideal for real-world clinical applications, as demonstrated in (Kavitha et al., 2023) in prenatal diagnosis. The language rules and fuzzy membership functions offer healthcare workers vital insights into the decision-making process (W. Wang et al., 2025), increasing trust and acceptability in critical situations. This robustness is especially useful in cases where data gathering and annotation processes are prone to errors and inconsistencies. Furthermore, fuzzy-based techniques excel at integrating varied healthcare data from multiple modalities (Y. Li et al., 2024), allowing for complete health analysis while retaining the ability to deal with noise and ambiguity typically seen in healthcare data.

Our review highlights how fuzzy logic provides several advantages that complement modern deep learning architectures. Fuzzy membership functions naturally represent the linguistic uncertainty inherent in medical data—concepts like “borderline hypertension” or “moderate progression” are fundamentally gradual rather than probabilistic (Shahbakhti et al., 2024). This interpretability addresses regulatory requirements for explainability (W. Wang et al., 2025) while enabling validation against clinical guidelines. Additionally, fuzzy methods demonstrate robust performance with limited data ($n < 200$), as shown in (Tzalavra et al., 2022), and naturally incorporate domain expertise through carefully designed membership functions and rules (Kumar et al., 2023). The resurgence of fuzzy research since 2023 reflects recognition that optimal approaches integrate fuzzy techniques within deep learning pipelines—using fuzzy preprocessing for uncertainty handling, fuzzy attention mechanisms for interpretable feature weighting (Ding et al., 2023), or fuzzy ensemble fusion for improved robustness (Mahanty et al., 2022).

The transferability of fuzzy models across healthcare disciplines provides a considerable implementation advantage (Jain & Srivastava, 2025). The modular architecture of fuzzy logic makes knowledge and experience transfer between applications easier, minimizing the need for costly retraining and hastening the adoption of breakthrough technology. This transferability encourages collaboration and knowledge sharing across several healthcare sectors, hence increasing efficiency and innovation. Finally, their ability to discover hidden rules in small datasets provides useful insights into complicated linkages and patterns, which improves the comprehension and interpretation of healthcare information across disciplines.

4.3. Current challenges and limitations

A fundamental challenge in fuzzy techniques lies in defining optimal membership functions, which form the core of fuzzy systems. The subjectivity in selecting membership function parameters can lead to suboptimal solutions. Recent research has shown promising advances in addressing this challenge. For instance, Shahbakhti et al. (Shahbakhti et al., 2024) demonstrated how combining fuzzy entropy with Gaussian and exponential membership functions can significantly improve performance in EEG analysis for anesthesia monitoring. The subjectivity in selecting membership function parameters can lead to suboptimal solutions, but adaptive approaches have emerged to address this limitation. Notably, Lyu et al. (Lyu et al., 2025) proposed a deep neuro-fuzzy method that effectively learns membership functions directly from ECG data through multimodal feature fusion. The extraction of rules from complex datasets presents another significant challenge, often limiting generalizability and reducing performance on unseen data. However, innovative solutions like the MKTC-R0T method (C. Wang et al., 2024) that have shown how zero-order TSK fuzzy systems can effectively handle this challenge while maintaining interpretability. Furthermore, Chowdhary et al. (Chowdhary et al., 2020) demonstrated that intuitionistic possibilistic fuzzy clustering combined with fuzzy SVM can achieve superior classification accuracy while preserving the interpretable nature of fuzzy systems. These advances suggest that systematic and adaptive methods for membership function optimization are not only possible but can significantly enhance the performance of fuzzy systems in healthcare applications.

While combining fuzzy methods with *meta*-heuristic optimization has shown promise (Sathiya & Sathiyabhama, 2019), the increased computational demands can prove problematic for time-sensitive medical applications. For this reason, careful consideration must be given to the computational overhead in terms of training time and inference latency. Recent studies have demonstrated that these computational demands can be effectively managed through two main strategies: (1) using lightweight *meta*-heuristics like Particle Swarm Optimization (PSO) (Tzalavra et al., 2022), and (2) implementing strategic sequencing of fuzzy and deep learning components, such as performing fuzzy clustering before the training phase (Kumar et al., 2023). The key is to balance the additional computational cost against the improved modeling capabilities offered by hybrid approaches, especially in applications where real-time processing is crucial.

The efficiency of fuzzy approaches varies greatly across healthcare datasets, making it difficult to produce consistent findings. Many studies rely on limited or single-dataset validation, raising questions about their broader applicability. This limitation becomes particularly apparent when comparing results across different medical domains, suggesting a need for more comprehensive validation approaches.

A fundamental limitation observed across the reviewed literature is the scarcity of studies reporting actual clinical deployment and prospective validation. The overwhelming majority of papers (>90%) evaluate their fuzzy-based systems exclusively on retrospective benchmark datasets, with limited discussion of regulatory pathways, clinical workflow integration, or real-world performance degradation. Critically, only a small fraction of studies (approximately 15%) employed external validation on independent datasets, and even fewer (< 5%) reported multi-center validation or prospective clinical testing. This reliance on single-dataset, retrospective evaluation creates substantial uncertainty about generalizability and real-world applicability. Moreover, computational requirements, inference latency, and hardware specifications, that are essential considerations for clinical deployment, were rarely reported, further widening the gap between research prototypes and deployable clinical tools. This research-to-practice gap represents a critical challenge for the field, as high benchmark accuracy does not guarantee clinical utility, regulatory approval, or clinical adoption. All these aspects limit our ability to assess the true clinical readiness of these systems. Future research must prioritize prospective clinical validation, multi-center testing, external dataset evaluation, and transparent reporting of both technical performance and clinical implementation challenges, including computational costs and integration requirements.

4.4. Future directions

This review of fuzzy techniques for healthcare applications reveals several promising opportunities for future advancement. Our analysis has identified key priorities that need to be addressed to advance the field, reflecting both current technical limitations and emerging clinical needs.

A primary challenge is enhancing the generalizability of fuzzy systems, especially for complex medical datasets. After an initial focus on achieving high performance with "pure" deep learning approaches, recent years (2023–2025) show increased attention to reliability and interpretability. Hybrid approaches that integrate fuzzy logic with deep learning architectures could combine the interpretability of fuzzy rules with the powerful representational capabilities of deep neural networks (Kumar et al., 2023), (Tzalavra et al., 2022). This fusion may enable more effective extraction of rules from intricate, multidimensional medical data.

Another major problem is to reduce the computing complexity of fuzzy models so that they can be used in real-time clinical settings, as highlighted in recent studies (Sathiya & Sathiyabhama, 2019). Developing efficient algorithms and optimization methodologies will help to reduce processing time while preserving accuracy and flexibility in dealing with uncertainty.

There is also a lot of space for innovation in using fuzzy techniques to evaluate healthcare data such as EEG, ECG, and EMG (C. Wang et al., 2024). Tailored feature extraction techniques based on domain expertise and biomedically inspired fuzzy set design may improve signal detection and pattern identification (Y. Li et al., 2024), resulting in more accurate patient monitoring and diagnosis.

Furthermore, enhancing the interpretability of fuzzy systems through refined, intuitive linguistic rules and membership functions will be hugely impactful (De Campos Souza & Lughofer, 2020). This will provide transparency into fuzzy model reasoning, increasing trustworthiness and adoption among healthcare professionals.

Robust frameworks leveraging fuzzy logic also exhibit potential for integrating multimodal patient data, including images, signals, electronic records, genomic data, and text reports (Lyu et al., 2025). By accounting for correlations and uncertainties, fuzzy systems can enable holistic analysis of diverse healthcare data types.

Optimized fuzzy inference systems capable of rapidly processing streaming data might considerably enhance real-time clinical decision support and surgical guidance in critical situations. Fuzzy logic integrated into clinical support systems has the ability to supplement human competence by incorporating imprecise information and medical expertise.

Additionally, fuzzy techniques show promise for predictive analytics and prognosis applications by using patient and genomic data. Finally, collaborative approaches like federated learning can enable fuzzy systems to leverage large, varied medical datasets for enhanced performance.

Key research questions that need to be addressed include:

- How to balance computational efficiency with model performance in clinical settings?
- What are the best approaches for integrating domain expertise into fuzzy system design?
- How can interpretability be enhanced while maintaining model accuracy?
- What are effective strategies for handling multimodal medical data in fuzzy systems?

5. Conclusion

This review highlights the journey of fuzzy techniques in medical data analysis over the past decade. What began as independent fuzzy logic solutions has evolved into sophisticated systems that complement modern AI architectures, improving both accuracy and interpretability of medical analysis. The transition has been particularly noteworthy in how fuzzy logic now enhances artificial intelligence applications, bringing both better accuracy and clearer interpretability to medical diagnostics. Our findings show impressive performance gains, especially in hybrid approaches. When fuzzy logic is combined with deep learning, we see accuracy consistently above 95% for medical imaging applications and exceeding 93% for biosignal analysis. These results demonstrate how effectively fuzzy methods can enhance ML approaches, merging the transparency of fuzzy logic with deep learning's powerful analytical capabilities. Despite these advances, several challenges need to be addressed. Important areas for improvement include better membership function optimization, lower computational costs, and more consistent performance across varied medical datasets. Future research should prioritize the development of more scalable systems without compromising interpretability, a key feature for medical applications. These trends suggest fuzzy techniques will continue playing an increasingly vital role in advancing healthcare technology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A:. Search strategy detail

To ensure comprehensive coverage of the literature, we developed specific search strings for each database, considering their individual syntax requirements and search capabilities. Our search strategy focused on capturing papers that combined fuzzy logic approaches with healthcare applications. The following search strings were used for each database, combining terms related to fuzzy techniques with healthcare-relevant keywords:

- PubMed: ("fuzzy logic"[Title/Abstract] OR "fuzzy system"[Title/Abstract] OR "fuzzy neural"[Title/Abstract]) AND ("healthcare"[Title/Abstract] OR "medical"[Title/Abstract] OR "clinical"[Title/Abstract] OR "diagnosis"[Title/Abstract] OR "disease"[Title/Abstract])
- Scopus: TITLE-ABS-KEY ("fuzzy logic" OR "fuzzy system" OR "fuzzy neural") AND TITLE-ABS-KEY ("healthcare" OR "medical" OR "clinical" OR "diagnosis" OR "disease")
- IEEE Xplore: ("fuzzy logic" OR "fuzzy system" OR "fuzzy neural") AND ("healthcare" OR "medical" OR "clinical" OR "diagnosis" OR "disease")

- Google Scholar: allintitle: (“fuzzy logic” OR “fuzzy system” OR “fuzzy neural”) AND (“healthcare” OR “medical” OR “clinical” OR “diagnosis” OR “disease”)

From each included study, we systematically extracted relevant information including publication details (authors, year, journal), study objective and healthcare application domain, dataset characteristics and size, fuzzy methodology details, validation strategy, performance metrics and results, and key findings and limitations.

Appendix B:. Study quality checklist

Each paper was evaluated against the following criteria.

Table B1
Quality assessment criteria.

Criterion	Excellent (3 points)	Good (2 points)	Basic (1 point)	Insufficient (0 points)
Methodological rigor	Complete methodology with detailed fuzzy system architecture, parameter settings, and implementation steps; fully reproducible	Clear methodology with most implementation details; largely reproducible	Basic methodology description with some gaps	Insufficient methodological details
Validation protocol	Large, diverse dataset ($n > 200$); clear validation protocol; multiple performance metrics; statistical significance testing	Adequate dataset ($50 < n < 200$); standard validation approach; basic performance metrics	Small dataset ($n < 50$); limited validation	Unclear validation or insufficient data
Clinical relevance	Direct clinical application; healthcare expert involvement; real-world implementation testing	Clear healthcare use case; some clinical input; theoretical implementation	General healthcare relevance; limited clinical perspective	Unclear healthcare application
Technical innovation	Novel fuzzy approach; comprehensive comparison with state-of-the-art; clear advantages demonstrated	Modified existing approach; basic comparisons; some advantages shown	Standard implementation; limited comparison	No innovation or comparison

Papers scoring below 9 points were excluded to maintain high quality standards across the review. This quality assessment framework ensured that only methodologically sound and clinically relevant studies were included in our review, maintaining high standards across all analyzed papers.

Appendix C:. Reviewed studies

.

Table C1
Studies with fuzzy-based MR image analysis (n = 31).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Kaur et al. (Kaur et al., 2019), 2019	Parkinson’s disease detection	1. BRATS 2012: 120 images 2. Harvard Medical School Repository: 276 images 3. KEEL datasets: 160 images	Hybrid fuzzy-ML approach	Fisher + Parameter-Free BAT algorithm, adaptive fuzzy K-nearest neighbor	5-fold CV	1. A: 100.00 2. A: 100.00 3. A: 98.00
Alam et al. (Alam et al., 2019), 2019	Brain tumor detection	Private dataset: 40 images	Traditional fuzzy system	The template-based K means and improved fuzzy C means	50:50	A: 97.50
Hermessi et al. (Hermessi et al., 2019), 2019	Soft tissue sarcoma classification	The Cancer Imaging Archive dataset: 21 patients, 4338 MRI scans	Traditional fuzzy system	Convolutional neural network, stochastic gradient descent, type-2 fuzzy sets	5-fold CV	A: 98.28
Ozyurt et al. (Özyurt et al., 2019), 2019	Brain tumor detection	TCGA-GBM: 160 images	Hybrid fuzzy-ML approach	CNN, neutrosophic expert maximum fuzzy sure entropy, SVM	5-fold CV	A: 95.62
Sert et al. (Sert et al., 2019), 2019	Brain tumor detection	TCGA-GBM: 200 images	Fuzzy-enhanced deep learning	Maximum fuzzy entropy segmentation, convolutional neural network	5-fold CV	A: 95.00
Raja and Rani (Siva Raja & Rani, 2020), 2020	Brain tumor detection	BRATS 2015: 200 images	Fuzzy-enhanced deep learning	Bayesian fuzzy clustering algorithm with hybrid deep autoencoder	5-fold CV	A: 98.50
Narmatha et al. (Narmatha et al., 2020), 2020	Brain tumors detection	BRATs 2018: 351 images	Hybrid fuzzy-ML approach	Fuzzy brain-storm optimization algorithm, Fuzzy C-mean clustering	72:18 (train-test split)	A: 93.85
Huang et al. (Huang et al., 2020), 2020	Parkinson’s disease detection	The Image and Data Archive (IDA): 9 MRI for each PD patient	Hybrid fuzzy-ML approach	Adaptive K-means clustering algorithm, fuzzy c-means algorithm	N.A.	JSC: 92.00 MSE: 63.49
Ghasemi et al. (Ghasemi et al., 2020a), 2020	1. Brain tumor detection 2. Cancer genome atlas 3. Breast cancer	1. TCIA: 130 patients, 110,020 images 2. TCGA-LGG: 199 patients, 2275 images 3. MIAS: 322 images	Hybrid fuzzy-ML approach	Fuzzy discriminative sparse coding, Principal component analysis	80:20 (train-test split)	1. A: 99.27 2. A: 98.38 3. A: 99.18
Ozyurt et al. (Özyurt et al., 2020), 2020	Brain tumor detection	TCGA-GBM: 300 images	Fuzzy-enhanced deep learning	Fuzzy C-means, convolutional neural network, extreme learning machine	10-fold CV	A: 98.33

(continued on next page)

Table C1 (*continued*)

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Reddy et al. (G. T. Reddy et al., 2020), 2020	Brain tumor detection	Harvard Medical School and Kaggle, for a total of 235 images	Traditional fuzzy system	Hybrid genetic algorithm with fuzzy logic classifier	80:20 (train-test split)	A: 90.00
Ghasemi et al. (Ghasemi et al., 2020b), 2020	1. Brain tumor detection 2. Cancer genome atlas	1. TCIA: 4095 images 2. TCGA-LGG: 3289 images	Hybrid fuzzy-ML approach	Type-2 fuzzy learning with sparse representation	8-fold CV	1. A: 99.33 2. A: 99.52
Bae et al. (Bae et al., 2021), 2021	Brain segmentation	TSE BLADE datasets 1. 2D imaging: 9 subjects 2. 3D imaging: 16 subjects Total: 4905 images	Traditional fuzzy system	Fuzzy c-means thresholding	80:20 (train-test split)	1. DC: 96.50 2. DC: 97.46
Ghasemi et al. (Ghasemi et al., 2021), 2021	1. Brain tumor detection 2. Cancer genome atlas 3. Breast cancer	1. REMBRANDT: 330 patients, 110,020 images 2. TCGA-LGG: 199 patients, 241,183 images 3. MIAS: 322 images	Hybrid fuzzy-ML approach	Adaptive fuzzy dictionary learning with sparse representation	80:20 (train-test split)	1. A: 98.31 2. A: 98.59 3. A: 98.04
Khosravanian et al. (Khosravanian et al., 2021), 2021	Glioma brain tumor segmentation	BraTS 2017: 285 patients	Hybrid fuzzy-ML approach	Superpixel fuzzy clustering, lattice Boltzmann method	N.A.	DC: 93.04
Togacar et al. (Toğaçar et al., 2021), 2021	Alzheimer's disease stages detection	The AD dataset	Hybrid fuzzy-ML approach	Fuzzy color image enhancement, hypercolumn techniques, SVM	75:25 (train-test split)	A: 99.94
Alhassan et al. (Alhassan et al., 2022), 2022	Alzheimer's disease diagnosis	1. ADNI: 1193 patients 2. Australian Imaging Biomarkers and Lifestyle: 496 images	Hybrid fuzzy-ML approach	Fuzzy elephant herding optimization, Otsu segmentation	N.A.	1. A: 94.20 2. A: 86.5
Sathish and Elango (Sathish & Elango, 2022), 2022	Brain tumor classification	1. BRATS: 65 images 2. SIMBRATS: 50 images	Hybrid fuzzy-ML approach	Gaussian hybrid fuzzy clustering, radial basis neural network	10-fold CV	1. A: 89.52 2. A: 87.19
Usha et al. (Padma Usha et al., 2022), 2022	Brain tumor detection	Private: 60 images	Fuzzy-enhanced deep learning	Berkeley's wavelet convolutional transfer learning, local binary Gabor fuzzy C-means clustering	70:30 (train-test split)	A: 98.70
Tzalavra et al. (Tzalavra et al., 2022), 2022	Breast tumor classification	Private: 60 patients	Fuzzy-enhanced deep learning	Hybrid adaptive neuro-fuzzy inference system, particle swarm optimization	67:33 (train-test split)	A: 94.00
Rezaie and Parnianifard (Rezaie & Parnianifard, 2022), 2022	Brain tumor detection	Private: 60 images	Hybrid fuzzy-ML approach	Type-2 fuzzy neural network, Gray Level Co-occurrence Matrix	67:33 (train-test split)	A: 98.96
Ouchicha et al. (Ouchicha et al., 2023), 2023	Brain tumor segmentation	BrainWeb	Traditional fuzzy system	Modified kernel fuzzy c-means clustering, Modified Kernel with Exponential Entropy	N.A.	DC: 92.62
Reddy and Dhuli (K. R. Reddy & Dhuli, 2023), 2023	Brain tumors detection	Harvard Medical School and Kaggle, for a total of 235 images	Hybrid fuzzy-ML approach	Spatial fuzzy c-means threshold, local binary pattern and classification with Random Forest and Logit-Boost Ensemble Learning	70:30 (train-test split)	A: 95.71
Reddy N. et al. (N. et al., 2024), 2024	Brain tumor segmentation and classification	Harvard Medical School Dataset + Kaggle Repository Dataset, for a total of 235 images	Traditional fuzzy system	Spatial Fuzzy C-Means (SFCM) clustering for image segmentation	80:20 (train-test split)	DSC: 92.15, A: 100%
Singh et al. (Singh et al., 2024), 2024	Brain MRI segmentation	1. IBSR: 256 images 2. Brainweb: 181 images	Traditional fuzzy system	Local parameter-free fuzzy factor, Intuitionistic fuzzy set theory, Fuzzy c-means with intensity inhomogeneity correction	N.A.	1. DC: 85.68 2. DC: 94.56
Neelima et al. (Neelima et al., 2024), 2024	Brain tumor classification	BraTS dataset	Fuzzy-enhanced deep learning	Optimized deep neuro-fuzzy network, convolutional neural network	80:20 (train-test split)	A: 91.50
Jafrasteh et al. (Jafrasteh et al., 2024), 2024	Brain tissue segmentation (WM, GM, CSF)-MRI	1. BrainWeb: 20 images 2. IBSR: 18 images 3. HUPM: 3 images 4. IXI: 581 images	Hybrid fuzzy-ML approach	Enhanced Spatial Fuzzy C-means (esFCM), Weighted least square with SSIM for bias field correction	Cross-dataset validation	DC: 85.08
Alagarsamy et al. (Alagarsamy et al., 2024), 2024	Brain tumor segmentation-MRI	1. BRATS 2017: 100 images 2. BRATS 2018: 150 images 3. BRATS 2020 4. Private dataset: 300 images	Hybrid fuzzy-ML approach	Firefly algorithm, Interval type-II fuzzy logic system	Cross-dataset validation	DC: 97.00
Mayeta-Revilla et al. (Mayeta-Revilla et al., 2025), 2025	Brain tumor segmentation and classification	BraTS2020: 366 patients	Fuzzy-enhanced deep learning	ANFIS combines fuzzy logic (Takagi-Sugeno model) with CNN learning	80:20 (train-test split)	DC: 82.94 (tumor core)A: 95.43 (binary classification) ,A: 92.14 (multi-class)

(continued on next page)

Table C1 (*continued*)

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
M R. et al. (M et al., 2025), 2025	Early AD stages diagnosis-MRI	ADNI 1: 30 images ADNI 3: 10 images	Hybrid fuzzy-ML approach	VolBrain automated segmentation, 10 volumetric features, FIS and ANFIS variants	5-fold CV	A: 84.79
Xiao et al. (L. Xiao et al., 2025), 2025	ASD classification-fMRI	ABIDE: 1120 patients	Fuzzy-enhanced deep learning	Multi-site contrast learning domain adaptive TSK fuzzy system, Contrastive learning strategy	80:20 (train-test split)	A: 88.00

A: Accuracy; ANFIS: Adaptive Neuro-Fuzzy Inference System; CC: Correlation Coefficient; CNN: Convolutional Neural Network; CV: Cross-Validation; DC: Dice Coefficient; FIS: Fuzzy Inference System; JSC: Jaccard Index; N.A.: Not Available; SSIM: Structural Similarity Index Measure; SVM: Support Vector Machine.

Table C2
Studies with fuzzy-based CT image analysis (n = 11).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Manikandan and Bharathi (Manikandan & Bharathi, 2016), 2016	Lung cancer detection	ELCAP: 50 images, Bharat Scan Centre: 106 images	Traditional fuzzy system	Fuzzy auto-seed cluster means morphological segmentation	60:40 (train-test split)	A: 94.00
Farahani et al. (Farahani et al., 2018), 2018	Lung nodule detection	LIDC: 120 CT images	Hybrid fuzzy-ML approach	Modified spatial kernelized fuzzy c-means with ensemble classifier	N.A.	A: 95.02
Das et al. (A. Das et al., 2019), 2019	Liver cancer detection	Private: 123 images	Hybrid fuzzy-ML approach	Modified Fuzzy Clustering, local binary pattern, decision tree	10-fold CV	A: 95.8
Sathiya and Sathiyabhama (Sathiya & Sathiyabhama, 2019), 2019	Lung nodule detection	LIDC/IDRI dataset: 1018 CT images	Hybrid fuzzy-ML approach	Gabor convolution, Circular local binary pattern, Particle swarm optimization	10-fold CV	A: 98.75
Manickavasagam and Selvan (Manickavasagam & Selvan, 2019), 2019	Lung nodule detection	Private: 275 images	Hybrid fuzzy-ML approach	Cuckoo search algorithm with optimized neuro fuzzy classifier	80:20 (train-test split)	A: 97.79
Veronica (Veronica, 2020), 2020	Lung nodule detection	ELCAP: 50 images	Hybrid fuzzy-ML approach	Fuzzy C-Means, Oppositional-based Ant-Lion Optimization, ANN	N.A.	A: 86.60
Kundu et al. (Kundu et al., 2021), 2021	COVID-19 diagnosis	SARS-CoV-2 CT-Scan Dataset: 2481 CT images	Fuzzy-enhanced deep learning	Fuzzy integral-based convolutional neural network ensemble	70:30 (train-test split)	A: 98.93
Song et al. (Song et al., 2022), 2022	COVID-19 diagnosis	COVID-CT-Dataset: 620 images	Fuzzy-enhanced deep learning	Convolutional neural network, deep fuzzy model	80:20 (train-test split)	A: 94.17
Chharia et al. (Chharia et al., 2022), 2022	COVID-19 diagnosis	1. COVID-Chestxray-dataset: 392 CT images 2. Kaggle-chest-xray-dataset: 588 CT images	Fuzzy-enhanced deep learning	Biologically-inspired conv-fuzzy network	15-fold CV	1. A: 97.47 2. A: 90.68
Mahanty et al. (Mahanty et al., 2022), 2022	COVID-19 detection	China National Center for Bio-information: 1950 images	Fuzzy-enhanced deep learning	Convolutional neural network, Sugeno fuzzy integral	70:30 (train-test split)	A: 99.15
Li et al. (L. Li et al., 2024), 2024	Tumor co-segmentation-PET/CT	1. HECKTOR: 325 patients 2. NSCLC: 50 patients	Hybrid fuzzy-ML approach	Fuzzy C-means clustering, Bayesian classification, Novel grayscale similar region term, Edge stop function	70:30 (train-test split)	1. DC: 0.85 2. DC: 0.86

A: Accuracy; ANN: Artificial Neural Network; CT: Computed Tomography; CV: Cross-Validation; D: Dice coefficient; N.A.: Not Available; PET: Positron Emission Tomography; NSCLC: Non-Small Cell Lung Cancer.

Table C3
Studies with fuzzy-based analysis of other medical imaging modalities (n = 13).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Almotiri et al. (Almotiri et al., 2018), 2018	Retinal structure segmentation	1. DRIVE: 80 fundus images 2. STARE: 20 fundus images 3. DRISHTI-GS: 50 fundus images 4. DIARETDB1: 89 fundus images	Hybrid fuzzy-ML approach	Morphological adaptive fuzzy thresholding	10-fold CV	1. A: 95.88 2. A: 94.02 3. FLS: 90.20 4. A: 83.40
Son et al. (Son et al., 2018), 2018	Dental disease segmentation	Private: 87 dental X-ray images	Hybrid fuzzy-ML approach	Semi-Supervised fuzzy clustering, local binary pattern	10-fold CV	A: 92.74
Nida et al. (Nida et al., 2019), 2019	Melanoma lesion detection and segmentation	ISIC-2016: 1280 dermoscopic images	Hybrid fuzzy-ML approach	Fuzzy C-means clustering, convolutional neural network	80:20 (train-test split)	A: 94.00
Hassan et al. (Hassan et al., 2019), 2019	1. Brain segmentation 2. Carotid artery plaque detection	1. BrainWeb: 20 MR images 2. Carotid artery ultrasound dataset: 250 images	Hybrid fuzzy-ML approach	Fuzzy intelligence, Gaussian mixture model	N.A.	1. A: 99.20 2. A: 98.80

(*continued on next page*)

Table C3 (*continued*)

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Memari et al. (Memari et al., 2019), 2019	Retinal blood vessel segmentation	1. DRIVE: 40 fundus images 2. STARE: 20 fundus images 3. CHASE_DB1: 28 fundus images	Hybrid fuzzy-ML approach	Fuzzy C-means Clustering, Matched Filtering	50:50	1. A: 96.10 2. A: 95.10 3. A: 93.90
Chowdhary et al. (Chowdhary et al., 2020), 2020	Breast cancer segmentation	MIAS: 320 mammography images	Hybrid fuzzy-ML approach	Intuitionist possibilistic Fuzzy C-Mean Clustering, fuzzy support vector machine	N.A.	A: 98.85
Abdullah et al. (Abdullah et al., 2020), 2020	Human retina optic disc segmentation	1. DRIVE: 40 fundus images 2. STARE: 81 fundus images 3. DIARETDB1: 89 fundus images 4. DRIONS-DB: 110 fundus images	Traditional fuzzy system	Fuzzy clustering method	N.A.	1. A: 100.0 2. A: 97.53 3. A: 100.0 4.A: 100.0
Cai et al. (Cai et al., 2021), 2021	Medical image segmentation	1. ISIC 2017: 545 dermoscopic images 2. ISIC 2018: 45 dermoscopic images 3. Lung dataset 4. DRIVE: 40 fundus images	Fuzzy-enhanced deep learning	Quadratic polynomial guided fuzzy C-means, dual attention mechanism	5-fold CV	1. A: 96.01 2. A: 95.69 3. A: 99.82 4. A: 95.69
Ding et al. (Ding et al., 2023), 2023	Medical image segmentation	1. Lung segmentation dataset: 704 X-ray images 2. Gastrointestinal polyp segmentation: 1000 endoscopic images 3. Kidney segmentation dataset: 4586 CT images 4. Breast ultrasound images dataset: 788 images	Fuzzy-enhanced deep learning	Fusing Transformer, convolutional neural network	80:20 (train-test split)	1. A: 97.78 2. A: 96.76 3. A: 97.54 4. A: 96.60
Kavitha et al. (Kavitha et al., 2023), 2023	Prenatal HLHS diagnosis-ultrasound	Private: 993 4-chamber view ultrasound images	Hybrid fuzzy-ML approach	FMLET preprocessing, Morphological operations (open, close, thinning, thickening), Feature extraction (RVLVR, CTR)	ROC analysis	A: 91.00, AUC: 0.9137
Biesok et al. (Biesok et al., 2024), 2024	Breast tumor segmentation-ultrasound	993 breast ultrasound images from 3 public collections (BUSI, OASBUD, and private dataset)	Fuzzy-enhanced deep learning	Hybrid approach: Distance-adapted fuzzy connectedness, Autoencoder CNN, Chan-Vese active contour, autoencoder CNN	5-fold CV	DC: 0.79
Wang et al. (W. Wang et al., 2025), 2025	CLNM status prediction in PTC-ultrasound	Private: 1019 patients	Fuzzy-enhanced deep learning	Expert knowledge-guided deep fuzzy network	65:15:20 (train-val-test split)	AUC: 0.786, A: 0.745
Jiao et al. (Jiao et al., 2025), 2025	Breast tumor segmentation-ultrasound	1. BUSI 2. Private dataset	Fuzzy-enhanced deep learning	BS-Mamba architecture with three novel modules	N.A.	1. DC: 92.13, 2. DC: 92.62

A: Accuracy; AUC: Area Under the Curve; CNN: Convolutional Neural Network; CLNM: Cervical Lymph Node Metastasis; CTR: Cardiothoracic Ratio; DC: Dice coefficient; FLS: F1 Score; HLHS: Hypoplastic Left Heart Syndrome; N.A.: Not Available; PTC: Papillary Thyroid Carcinoma; ROC: Receiver Operating Characteristic; RVLVR: Right Ventricle to Left Ventricle Ratio.

Table C4
Studies with fuzzy-based EEG analysis (n = 18).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Kocadagli and Langari (Kocadagli & Langari, 2017), 2017	Epileptic seizures	Bonn: 500 EEG segments	Hybrid fuzzy-ML approach	Hybrid artificial neural networks, wavelet transforms and fuzzy relations, genetic algorithm, ANN	5-fold CV	A: 99.80
Jiang et al. (Jiang et al., 2017), 2017	Seizure classification- EEG signal classification	7,500 bivariate EEG signals	Hybrid fuzzy-ML approach	Takagi-Sugeno-Kang fuzzy system, SVM	10-fold CV	A: 99.5
Bhattacharyya et al. (Bhattacharyya et al., 2017), 2017	Focal EEG Signal Analysis	Bern–Barcelona EEG Dataset	Hybrid fuzzy-ML approach	Multivariate sub-band fuzzy entropy, Tunable-Q wavelet transform	10-fold CV	A: 84.67
Shalbaf et al. (Shalbaf et al., 2018), 2018	DoA monitoring-EEG	Private: 67 patients	Hybrid fuzzy-ML approach	Feature extraction (11 features), Best feature subset selection, ANFIS with linguistic hedges (ANFIS-LH)	Leave-one-out cross-validation	A: 92.00 (4-state classification),A: 93.00 (2-state classification)
Baskar et al. (Baskar et al., 2020), 2020	Cranial nerve palsy Detection- EEG signal classification	BONN: 500 EEG segments	Hybrid fuzzy-ML approach	Fuzzy based twofold graphic discrete wavelet transform, hybrid Fuzzy spearman rank correlation classifier	10-fold CV	A: 90.00
Amezquita-Sanchez et al. (Amezquita-	Dementia stages classification- EEG signal	135 patients	Traditional fuzzy system	Entropy and fuzzy logic system	Holdout validation	A: 86.90

(continued on next page)

Table C4 (*continued*)

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Sanchez et al., 2021), 2021						
Dhara et al. (Dhara et al., 2024), 2024	Emotion Recognition, EEG signal classification	1. DEAP: 32 patients, 2. AMIGOS: 40 patients	Fuzzy-enhanced deep learning	Fuzzy ensemble-based deep learning approach using Gompertz function, fuzzy ensemble of three deep learning models	60:20:20 (train-val-test split)	1. A: 95.00 (subject-dependent)2. A: 99.38 (subject-independent)
Li et al. (A. Li et al., 2024), 2024	Epilepsy detection-EEG signal classification	CHB-MIT: 24 patients	Hybrid fuzzy-ML approach	Multiview Information Preservation Transfer Representation Learning, Takagi-Sugeno-Kang fuzzy system	N.A.	A: 92.95
Li et al. (J. Li et al., 2024), 2024	Parkinson's disease detection-EEG signal classification	1. San Diego dataset: 31 patients 2. UNM dataset: 54 patients	Fuzzy-enhanced deep learning	Multi-scale fuzzy entropy (MSFEn), Two-dimensional multiple dual attention gated temporal-separable (2D-MDAGTS) model	80:20 (train-test split)	1. A: 98.68 (drug-free), A: 99.01 (medicated) 2. A: 99.30 (drug-free), A: 99.31 (medicated)
Shahbakhti et al. (Shahbakhti et al., 2024), 2024	Depth of anesthesia monitoring-EEG	Public: 24 patients	Traditional fuzzy system	Fuzzy entropy with Gaussian and exponential membership functions, EEG subband decomposition, regressor	10-fold CV	CC: 0.85, Mean absolute error: 5.4
Wang et al. (C. Wang et al., 2024), 2024	Epileptic EEG classification	Bonn: 12 EEG signals	Traditional fuzzy system	Multicenter Knowledge Transfer Calibration with rapid zeroth-order TSK fuzzy system	80:20 (train-test split)	A: 84.05
Versaci and La Foresta (Versaci & La Foresta, 2024), 2024	EEG classification for Alzheimer's disease detection	Private dataset	Fuzzy-enhanced deep learning	Fuzzy logic techniques, Intuitionistic fuzzy systems, Neural networks	N.A.	N.A
Cataldo et al. (Cataldo et al., 2024), 2024	Alzheimer's disease detection-EEG signal classification	CAUEEG: 70 patients; TUH EEG: 34 patients	Traditional fuzzy system	Multiscale fuzzy entropy (MFE), Brain complexity analysis, MFE-based detection algorithm	80:20 (train-test split)	A: 83.00, Matthews correlation: 0.67
Khan et al. (Khan et al., 2024), 2024	Epilepsy detection-EEG signal classification	Private: 23 subjects, 49 EEG recordings	Fuzzy-enhanced deep learning	Fuzzy deep learning (FDL), LIME, SHAP, explainable fuzzy deep learning model	70:15:15 (train-val-test split)	A: 92.57
Li et al. (Y. Li et al., 2024), 2024	Depression recognition-EEG	Bonn: 500 EEG segments	Hybrid fuzzy-ML approach	Functional Connection Feature Selection with Fuzzy Label (FLFCFS), Phase lag index (PLI), Functional connectivity, SVM	10-fold CV	A: 92.59
Kalpana and Mohanbabu (Kalpana & Mohanbabu, 2024), 2024	EEG-based epileptic seizure detection	Bonn dataset	Hybrid fuzzy-ML approach	Possibility-based clustering with competitive learning (PC-CL), TSK fuzzy system	70:30 (train-test split)	A: 99.41
Arpaia et al. (Arpaia et al., 2025), 2025	Alzheimer's disease detection-EEG	CAUEEG: 70 patients and TUH: 34 patients	Traditional fuzzy system	Multiscale Fuzzy Entropy (MFE), Signal amplitude preprocessing, Amplitude transformation/ normalization, SVM, KNN	70:30 (train-test split)	A: 84.00
Jain and Srivastava (Jain & Srivastava, 2025), 2025	Multiple neurological disorders detection (epilepsy, Parkinson's, Alzheimer's, schizophrenia, stroke)-EEG classification	Five different public datasets for a total of 15,437 neurological signals	Hybrid fuzzy-ML approach	Fuzzy Logic and Spiking Neural Networks (FLSNN) with preprocessing for noise/ artifact removal	60:20:20 (train-val-test split)	A: 97.46 (binary classification)A: 98.87 (multi-class)

A: Accuracy; AD: Alzheimer's Disease; ANFIS: Adaptive Neuro-Fuzzy Inference System; ANN: Artificial Neural Network; CC: Correlation Coefficient; CV: Cross-Validation;DoA: Depth of Anesthesia; EEG: Electroencephalogram; KNN: K-Nearest Neighbors; LIME: Local Interpretable Model-agnostic Explanations; N.A.: Not Available; SHAP: SHapley Additive exPlanations; SVM: Support Vector Machine; TSK: Takagi-Sugeno-Kang.

Table C5
Studies with fuzzy-based ECG analysis (n = 8).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Muthuvel et al. (Muthuvel et al., 2019), 2019	ECG Beat classification	MIT-BIH Arrhythmia Database: 47 patients	Hybrid fuzzy-ML approach	Artificial bee colony, genetic algorithm, neuro-fuzzy classifier	N.A.	A: 93.00
Raminez et al. (Ramirez et al., 2019), 2019	2-lead cardiac arrhythmia classification	MIT-BIH Arrhythmia Database: 1,000 heartbeats	Hybrid fuzzy-ML approach	Type-1 FIS and IT2FIS, Fuzzy logic and neural networks	10-fold CV	A: 94.30

(continued on next page)

Table C5 (*continued*)

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Rabcan et al. (Rabcan et al., 2022), 2022	ECG preprocessing for arrhythmia and heart condition detection	Private	Hybrid fuzzy-ML approach	Fuzzification using FEBFC algorithm	N.A.	A: 93.80
Kumar et al. (Kumar et al., 2023), 2023	Arrhythmia detection	1. MIT-BIH: 401 samples 2. PTB Diagnostic ECG Dataset: 10,047 samples	Hybrid fuzzy-ML approach	Coupled fuzzy clustering and deep neural networks	80:20 (train-test split)	1. A: 98.66 2. A: 95.79
Abagaro et al. (Abagaro et al., 2024), 2024	ECG signal classification for cardiac abnormality detection	MIT-BIH Arrhythmia Database: 90,460 samples	Hybrid fuzzy-ML approach	Discrete wavelet transform (DWT), Principal component analysis (PCA), Adaptive neuro-fuzzy inference system (ANFIS)	62:38 (train-test split)	A: 99.44, Se: 99.36, Sp: 99.84
Lyu et al. (Lyu et al., 2025), 2025	ECG signal classification for cardiac arrhythmia detection	MIT-BIH arrhythmia database: 90,460 samples	Fuzzy-enhanced deep learning	Multimodal feature fusion, Transformer-based architecture, Deep neuro-fuzzy system	Ablation studies	A: 98.46, F1: 99.10
Rabcan et al. (Rabcan et al., 2025), 2025	ECG signal classification	Private: 111 patients	Hybrid fuzzy-ML approach	Preprocessing focusing on minimizing information loss and Fuzzy classifier	Hold-out validation	A: 0.86–1.00
Wang et al. (X. Wang et al., 2025), 2025	ECG arrhythmia classification	MIT-BIH Arrhythmia Database: 47 subjects	Fuzzy-enhanced deep learning	Multiscale deep neuro-fuzzy network (MDNFN), Particle swarm optimization, Multiscale feature extraction	60:40 (train-test split)	A: 86.83–98.97

A: Accuracy; ANFIS: Adaptive Neuro-Fuzzy Inference System; CV: Cross-Validation; DWT: Discrete Wavelet Transform; ECG: Electrocardiogram; F1: F1 Score; FIS: Fuzzy Inference System; IT2FIS: Interval Type-2 Fuzzy Inference System; MDNFN: Multiscale Deep Neuro-Fuzzy Network; N.A.: Not Available; PCA: Principal Component Analysis; Se: Sensitivity; Sp: Specificity.

Table C6
Studies with fuzzy-based analysis of other signal modalities (n = 7).

Author	Objective	Dataset	Fuzzy integration type	Methods	Validation strategy	Results (%)
Vallejo et al. (Vallejo et al., 2018), 2018	Neuromuscular disease detection- electromyography signals	EMGLAB: 120 EMG recordings	Traditional fuzzy system	Time-frequency analysis, fuzzy Entropy, neural networks, ANN	70:30 (train-test split)	A: 98.00
de Campos Souza (De Campos Souza & Lughofer, 2020), 2020	Heart murmurs detection from heart sound recordings	Combined dataset (University of Michigan + PhysioNet/CinC Challenge 2016 + eGeneral Medical Inc.) with > 10 K samples	Hybrid fuzzy-ML approach	Evolving fuzzy neural network with logical neurons (EFNN-LN), self-organizing fuzzy logic, feature weighting	10% offline training + 90% online sequential	A: 90.75
Soares et al. (Soares et al., 2020), 2020	Heart sound classification	PhysioNet/Computing in Cardiology Challenge 2016; 13,015 heart sound	Hybrid fuzzy-ML approach	Zero-order autonomous learning multiple-model, neuro-fuzzy method	10-fold CV	A: 93.04
Prabhakar et al. (Prabhakar et al., 2020), 2020	Cardiovascular disorders-Photoplethysmography signal classification	Capnobase dataset: 42 recordings	Hybrid fuzzy-ML approach	Fuzzy based animal migration optimization, SVM	10-fold CV	A: 95.05
Azadi et al. (Azadi et al., 2021), 2021	Parkinson's disease	224 voice phonation samples from 47 participants	Traditional fuzzy system	Interval type-2 fuzzy sets, fuzzy-based classification	10-fold CV	A: 95.32
Xiao et al. (F. Xiao et al., 2024), 2024	Cardiovascular disease diagnosis from heart sounds using a hybrid approach	1. PCCD (3240 recordings) 2. PHSD (528 recordings)	Fuzzy-enhanced deep learning	1D + 2D CNN with attention mechanism + manual features + evolving fuzzy system (SOFIS +)	10-fold CV	1. A: 96.3 2. A: 99.1
Yu et al. (Yu et al., 2025), 2025	Analysis of stroke and aging effects on neuromuscular system-EMG	Private: 31 patients	Hybrid fuzzy-ML approach	Refined fuzzy entropy, Refined composed multiscale fuzzy entropy, statistical methods	N.A.	Statistical difference in EMG signals between patients and controls

A: Accuracy; ANN: Artificial Neural Network; CV: Cross-Validation; EMG: Electromyography; FFDispEn: Fractional Fuzzy Dispersion Entropy; N.A.: Not Available; sEMG: Surface Electromyography; SVM: Support Vector Machine.

Data availability

Data will be made available on request.

References

MR, Ar, K., & SK. (2025). Diagnosing early stages of Alzheimer's diseases based on volumetric features from MRI using soft computing algorithms. *Multimedia Tools and Applications, 84*(35), 44811–44832. https://doi.org/10.1007/s11042-025-20732-2

Abagaro, A. M., Barki, H., Ayana, G., Dawud, A. A., Thamineni, B. L., Jemal, T., & Choe, S. (2024). Automated ECG signals analysis for cardiac abnormality detection and classification. *Journal of Electrical Engineering & Technology, 19*(5), 3355–3371. https://doi.org/10.1007/s42835-024-01902-y

Abdullah, A. S., Rahebi, J., Özok, Y. E., & Aljanabi, M. (2020). A new and effective method for human retina optic disc segmentation with fuzzy clustering method based on active contour model. *Medical & Biological Engineering & Computing, 58*(1), 25–37. https://doi.org/10.1007/s11517-019-02032-8

Ahmed, U., Issa, G. F., Khan, M. A., Aftab, S., Khan, M. F., Said, R. A. T., Ghazal, T. M., & Ahmad, M. (2022). Prediction of diabetes empowered with fused machine learning. *IEEE Access, 10*, 8529–8538. https://doi.org/10.1109/ACCESS.2022.3142097

Alagarsamy, S., Govindaraj, V., Shahina, A., & Nagarajan, D. (2024). Intelligent multigrade brain tumor identification in MRI: A metaheuristic-based uncertain set framework. *IEEE Transactions on Artificial Intelligence, 5*(11), 5381–5391. https://doi.org/10.1109/TAI.2024.3441520

Alam, M. S., Rahman, M. M., Hossain, M. A., Islam, M. K., Ahmed, K. M., Ahmed, K. T., Singh, B. C., & Miah, M. S. (2019). Automatic human brain tumor detection in MRI image using template-based K means and improved fuzzy C means clustering algorithm. *Big Data and Cognitive Computing, 3*(2), 27. https://doi.org/10.3390/bdcc3020027

Alhassan, A. M., The Alzheimer's Disease Neuroimaging Initiative, & The Australian Imaging Biomarkers and Lifestyle Flagship Study of Ageing. (2022). Enhanced Fuzzy Elephant Herding Optimization-Based OTSU Segmentation and Deep Learning for Alzheimer's Disease Diagnosis. *Mathematics*, *10*(8), 1259. https://doi.org/10.3390/math10081259.

Almotiri, J., Elleithy, K., & Elleithy, A. (2018). A multi-anatomical retinal structure segmentation system for automatic eye screening using morphological adaptive fuzzy thresholding. *IEEE Journal of Translational Engineering in Health and Medicine, 6*, 1–23. https://doi.org/10.1109/JTEHM.2018.2835315

Amezquita-Sanchez, J. P., Mammone, N., Morabito, F. C., & Adeli, H. (2021). A New dispersion entropy and fuzzy logic system methodology for automated classification of dementia stages using electroencephalograms. *Clinical Neurology and Neurosurgery, 201*, Article 106446. https://doi.org/10.1016/j.clineuro.2020.106446

Andonovski, G., Leite, D., Precup, R.-E., Gomide, F., Pratama, M., & Škrjanc, I. (2026). Advancements in data-driven evolving fuzzy and neuro-fuzzy control: A comprehensive survey. *Applied Soft Computing, 186*, Article 114058. https://doi.org/10.1016/j.asoc.2025.114058

Arpaia, P., Cacciapuoti, M., Cataldo, A., Criscuolo, S., De Benedetto, E., Masciullo, A., Pesola, M., & Schiavoni, R. (2025). Assessing the Role of EEG biosignal preprocessing to enhance multiscale fuzzy entropy in alzheimer's disease detection. *Biosensors, 15*(6), 374. https://doi.org/10.3390/bios15060374

Azadi, H., Akbarzadeh-T, M.-R., Kobravi, H.-R., & Shoeibi, A. (2021). Robust voice feature selection using interval type-2 fuzzy AHP for automated diagnosis of Parkinson's disease. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 29*, 2792–2802. https://doi.org/10.1109/TASLP.2021.3097215

Bae, I., Chae, J.-H., & Han, Y. (2021). A brain extraction algorithm for infant T2 weighted magnetic resonance images based on fuzzy c-means thresholding. *Scientific Reports, 11*(1), 23347. https://doi.org/10.1038/s41598-021-02722-0

Baskar, S., Dhulipala, V. R. S., Shakeel, P. M., Sridhar, K. P., & Kumar, R. (2020). Hybrid fuzzy based spearman rank correlation for cranial nerve palsy detection in MIoT environment. *Health and Technology, 10*(1), 259–270. https://doi.org/10.1007/s12553-019-00294-8

Bataineh, K. M., Naji, M., & Saqer, M. (2011). A comparison study between various fuzzy clustering algorithms. *Jordan Journal of Mechanical & Industrial Engineering, 5*(4).

Bhattacharyya, A., Pachori, R., & Acharya, U. (2017). Tunable-Q wavelet transform based multivariate sub-band fuzzy entropy with application to focal EEG signal analysis. *Entropy, 19*(3), 99. https://doi.org/10.3390/e19030099

Biesok, M., Juszczyk, J., & Badura, P. (2024). Breast tumor segmentation in ultrasound using distance-adapted fuzzy connectedness, convolutional neural network, and active contour. *Scientific Reports, 14*(1), 25859. https://doi.org/10.1038/s41598-024-76308-x

Buckley, J. J., & Hayashi, Y. (1994). Fuzzy neural networks: A survey. *Fuzzy Sets and Systems, 66*(1), 1–13. https://doi.org/10.1016/0165-0114(94)90297-6

Cai, W., Zhai, B., Liu, Y., Liu, R., & Ning, X. (2021). Quadratic polynomial guided fuzzy C-means and dual attention mechanism for medical image segmentation. *Displays, 70*, Article 102106. https://doi.org/10.1016/j.displa.2021.102106

Cataldo, A., Criscuolo, S., De Benedetto, E., Masciullo, A., Pesola, M., & Schiavoni, R. (2024). A novel metric for Alzheimer's disease detection based on brain complexity analysis via multiscale fuzzy entropy. *Bioengineering, 11*(4), 324. https://doi.org/10.3390/bioengineering11040324

Chatterjee, S., Chakrabarty, D., & Mukhopadhyay, A. (2022). Fuzzy association analysis for identifying climatic and socio-demographic factors impacting the spread of COVID-19. *Methods, 203*, 511–522. https://doi.org/10.1016/j.ymeth.2021.08.005

Chen, C. L. P., Zhang, C.-Y., Chen, L., & Gan, M. (2015). Fuzzy restricted boltzmann machine for the enhancement of deep learning. *IEEE Transactions on Fuzzy Systems, 23*(6), 2163–2173. https://doi.org/10.1109/TFUZZ.2015.2406889

Chharia, A., Upadhyay, R., Kumar, V., Cheng, C., Zhang, J., Wang, T., & Xu, M. (2022). Deep-precognitive diagnosis: preventing future pandemics by novel disease detection with biologically-inspired conv-fuzzy network. *IEEE Access, 10*, 23167–23185. https://doi.org/10.1109/ACCESS.2022.3153059

Chowdhary, C. L., Mittal, M., Pattanaik, P. A., & Marszalek, Z. (2020). An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-Mean clustering and fuzzy SVM algorithm. *Sensors, 20*(14), 3903. https://doi.org/10.3390/s20143903

Das, A., Das, P., Panda, S. S., & Sabut, S. (2019). Detection of Liver Cancer using Modified Fuzzy Clustering and Decision tree Classifier in CT Images. *Pattern Recognition and Image Analysis, 29*(2), 201–211. https://doi.org/10.1134/S1054661819020056

Das, R., Sen, S., & Maulik, U. (2021). A survey on fuzzy deep neural networks. *ACM Computing Surveys, 53*(3), 1–25. https://doi.org/10.1145/3369798

De Campos Souza, P. V., & Lughofer, E. (2020). Identification of Heart sounds with an Interpretable Evolving Fuzzy Neural Network. *Sensors, 20*(22), 6477. https://doi.org/10.3390/s20226477

Deng, Y., Ren, Z., Kong, Y., Bao, F., & Dai, Q. (2017). A hierarchical fused fuzzy deep neural network for data classification. *IEEE Transactions on Fuzzy Systems, 25*(4), 1006–1012. https://doi.org/10.1109/TFUZZ.2016.2574915

Dhara, T., Singh, P. K., & Mahmud, M. (2024). A fuzzy ensemble-based deep learning model for EEG-based emotion recognition. *Cognitive Computation, 16*(3), 1364–1378. https://doi.org/10.1007/s12559-023-10171-2

Ding, W., Wang, H., Huang, J., Ju, H., Geng, Y., Lin, C.-T., & Pedrycz, W. (2023). FTransCNN: Fusing Transformer and a CNN based on fuzzy logic for uncertain medical image segmentation. *Information Fusion, 99*, Article 101880. https://doi.org/10.1016/j.inffus.2023.101880

Farahani, F. V., Ahmadi, A., & Zarandi, M. H. F. (2018). Hybrid intelligent approach for diagnosis of the lung nodule from CT images using spatial kernelized fuzzy c-means and ensemble learning. *Mathematics and Computers in Simulation, 149*, 48–68. https://doi.org/10.1016/j.matcom.2018.02.001

Fernández, A., López, V., Del Jesus, M. J., & Herrera, F. (2015). Revisiting evolutionary fuzzy systems: Taxonomy, applications, new trends and challenges. *Knowledge-Based Systems, 80*, 109–121. https://doi.org/10.1016/j.knosys.2015.01.013

Freudenberger, J., Hell, E., & Knüpfer, W. (2001). Perspectives of medical X-ray imaging. *Nucl Instrum Methods Phys Res Section A: Accelerators, Spectrometers, Detect Associated Equip, 466*(1), 99–104. https://doi.org/10.1016/S0168-9002(01)00831-2

Ghasemi, M., Kelarestaghi, M., Eshghi, F., & Sharifi, A. (2020a). FDSR: A new fuzzy discriminative sparse representation method for medical image classification. *Artificial Intelligence in Medicine, 106*, Article 101876. https://doi.org/10.1016/j.artmed.2020.101876

Ghasemi, M., Kelarestaghi, M., Eshghi, F., & Sharifi, A. (2020b). T2-FDL: A robust sparse representation method using adaptive type-2 fuzzy dictionary learning for medical image classification. *Expert Systems with Applications, 158*, Article 113500. https://doi.org/10.1016/j.eswa.2020.113500

Ghasemi, M., Kelarestaghi, M., Eshghi, F., & Sharifi, A. (2021). AFDL: A new adaptive fuzzy dictionary learning for medical image classification. *Pattern Analysis and Applications, 24*(1), 145–164. https://doi.org/10.1007/s10044-020-00909-1

Hassan, M., Murtza, I., Hira, A., Ali, S., & Kifayat, K. (2019). Robust spatial fuzzy GMM based MRI segmentation and carotid artery plaque detection in ultrasound images. *Computer Methods and Programs in Biomedicine, 175*, 179–192. https://doi.org/10.1016/j.cmpb.2019.04.026

Hermessi, H., Mourali, O., & Zagrouba, E. (2019). Deep feature learning for soft tissue sarcoma classification in MR images via transfer learning. *Expert Systems with Applications, 120*, 116–127. https://doi.org/10.1016/j.eswa.2018.11.025

Hong, D. H., & Choi, C.-H. (2000). Multicriteria fuzzy decision-making problems based on vague set theory. *Fuzzy Sets and Systems, 114*(1), 103–113. https://doi.org/10.1016/S0165-0114(98)00271-1

Hoque, N., Ahmed, H. A., Bhattacharyya, D. K., & Kalita, J. K. (2016). A Fuzzy Mutual Information-based Feature selection Method for Classification. *Fuzzy Information and Engineering, 8*(3), 355–384. https://doi.org/10.1016/j.fiae.2016.09.004

Huang, Y.-P., Singh, P., & Kuo, H.-C. (2020). A hybrid fuzzy clustering approach for the recognition and visualization of MRI images of Parkinson's disease. *IEEE Access, 8*, 25041–25051. https://doi.org/10.1109/ACCESS.2020.2969806

Ishibuchi, H. (2007). Multiobjective genetic fuzzy systems: review and future research directions. *IEEE International Fuzzy Systems Conference, 2007*, 1–6. https://doi.org/10.1109/FUZZY.2007.4295487

Jafrasteh, B., Lubián-Gutiérrez, M., Lubián-López, S. P., & Benavente-Fernández, I. (2024). Enhanced spatial fuzzy C-means algorithm for brain tissue segmentation in T1 images. *Neuroinformatics, 22*(4), 407–420. https://doi.org/10.1007/s12021-024-09661-x

Jain, S., & Srivastava, R. (2025). Electroencephalogram (EEG) based fuzzy logic and spiking neural networks (FLSNN) for advanced multiple neurological disorder diagnosis. *Brain Topography, 38*(3), 33. https://doi.org/10.1007/s10548-025-01106-1

Jang, J.-S.-R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics, 23*(3), 665–685. https://doi.org/10.1109/21.256541

Jiang, Y., Wu, D., Deng, Z., Qian, P., Wang, J., Wang, G., Chung, F.-L., Choi, K.-S., & Wang, S. (2017). Seizure classification from EEG signals using transfer learning, semi-supervised learning and TSK fuzzy system. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25*(12), 2270–2284. https://doi.org/10.1109/TNSRE.2017.2748388

Jiao, J., Jiao, J., & Li, Z. (2025). BS-mamba: A robust network for breast ultrasound image segmentation using mamba architecture. *International Journal of Pattern Recognition and Artificial Intelligence, 2540002*. https://doi.org/10.1142/S0218001425400026

Kalpana, C., & Mohanbabu, G. (2024). Integrated TSVM-TSK fusion for enhanced EEG-based epileptic seizure detection: Robust classifier with competitive learning. *Biomedical Signal Processing and Control, 96*, Article 106440. https://doi.org/10.1016/j.bspc.2024.106440

Karaboga, D., & Kaya, E. (2019). Adaptive network based fuzzy inference system (ANFIS) training approaches: A comprehensive survey. *Artificial Intelligence Review, 52*(4), 2263–2293. https://doi.org/10.1007/s10462-017-9610-2

Katti, G., Ara, S. A., & Shireen, A. (2011). Magnetic resonance imaging (MRI)–A review. *International Journal of Dental Clinics, 3*(1), 65–70.

Kaur, T., Saini, B. S., & Gupta, S. (2019). An adaptive fuzzy K-nearest neighbor approach for MR brain tumor image classification using parameter free bat optimization algorithm. *Multimedia Tools and Applications, 78*(15), 21853–21890. https://doi.org/10.1007/s11042-019-7498-3

Kavitha, D., Geetha, S., & Geetha, R. (2023). An adaptive neuro fuzzy methodology for the diagnosis of prenatal hypoplastic left heart syndrome from ultrasound images. *Multimedia Tools and Applications, 83*(10), 30755–30772. https://doi.org/10.1007/s11042-023-16682-2

Khan, F. A., Umar, Z., Jolfaei, A., & Tariq, M. (2024). Explainable fuzzy deep learning for prediction of epileptic seizures using EEG. *IEEE Transactions on Fuzzy Systems, 32*(10), 5428–5437. https://doi.org/10.1109/TFUZZ.2024.3434709

Khosravanian, A., Rahmanimanesh, M., Keshavarzi, P., & Mozaffari, S. (2021). Fast level set method for glioma brain tumor segmentation based on Superpixel fuzzy clustering and lattice Boltzmann method. *Computer Methods and Programs in Biomedicine, 198*, Article 105809. https://doi.org/10.1016/j.cmpb.2020.105809

Kocadagli, O., & Langari, R. (2017). Classification of EEG signals for epileptic seizures using hybrid artificial neural networks based wavelet transforms and fuzzy relations. *Expert Systems with Applications, 88*, 419–434. https://doi.org/10.1016/j.eswa.2017.07.020

Kumar, S., Mallik, A., Kumar, A., Ser, J. D., & Yang, G. (2023). Fuzz-ClustNet: Coupled fuzzy clustering and deep neural networks for Arrhythmia detection from ECG signals. *Computers in Biology and Medicine, 153*, Article 106511. https://doi.org/10.1016/j.compbiomed.2022.106511

Kundu, R., Singh, P. K., Mirjalili, S., & Sarkar, R. (2021). COVID-19 detection from lung CT-Scans using a fuzzy integral-based CNN ensemble. *Computers in Biology and Medicine, 138*, Article 104895. https://doi.org/10.1016/j.compbiomed.2021.104895

Leite, D., Frigeri, V., & Medeiros, R. (2021). Adaptive Gaussian Fuzzy Classifier for Real-Time Emotion Recognition in Computer Games. *2021 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, 1–6. https://doi.org/10.1109/LA-CCI48322.2021.9769842.

Li, A., Deng, Z., Zhang, W., Xiao, Z., Choi, K.-S., Liu, Y., Hu, S., & Wang, S. (2024). Multiview transfer representation learning with TSK fuzzy system for EEG epilepsy Detection. *IEEE Transactions on Fuzzy Systems, 32*(1), 38–52. https://doi.org/10.1109/TFUZZ.2023.3288479

Lin, C.-F., & Wang, S.-D. (2002). Fuzzy support vector machines. *IEEE Transactions on Neural Networks, 13*(2), 464–471. https://doi.org/10.1109/72.991432

Lyu, X., Rani, S., Manimurugan, S., & Feng, Y. (2025). A deep neuro-fuzzy method for ECG big data analysis via exploring multimodal feature fusion. *IEEE Transactions on Fuzzy Systems, 33*(1), 444–456. https://doi.org/10.1109/TFUZZ.2024.3416217

Mahanty, C., Kumar, R., & Patro, S. G. K. (2022). Internet of medical things-based COVID-19 detection in CT images fused with fuzzy ensemble and transfer learning models. *New Generation Computing, 40*(4), 1125–1141. https://doi.org/10.1007/s00354-022-00176-0

Manickavasagam, R., & Selvan, S. (2019). Automatic detection and classification of lung nodules in CT image using optimized neuro fuzzy classifier with cuckoo search algorithm. *Journal of Medical Systems, 43*(3), 77. https://doi.org/10.1007/s10916-019-1177-9

Manikandan, T., & Bharathi, N. (2016). Lung cancer detection using fuzzy auto-seed cluster means morphological segmentation and SVM classifier. *Journal of Medical Systems, 40*(7), 181. https://doi.org/10.1007/s10916-016-0539-9

Mayeta-Revilla, L., Cavieres, E. P., Salinas, M., Mellado, D., Ponce, S., Torres Moyano, F., Chabert, S., Querales, M., Sotelo, J., & Salas, R. (2025). Radiomics-driven neuro-fuzzy framework for rule generation to enhance explainability in MRI-based brain tumor segmentation. *Frontiers in Neuroinformatics, 19*, Article 1550432. https://doi.org/10.3389/fninf.2025.1550432

Memari, N., Ramli, A. R., Saripan, M. I. B., Mashohor, S., & Moghbel, M. (2019). Retinal blood vessel segmentation by using matched filtering and fuzzy c-means clustering with integrated level set method for diabetic retinopathy assessment. *Journal of Medical and Biological Engineering, 39*(5), 713–731. https://doi.org/10.1007/s40846-018-0454-2

Muthuvel, K., Anto, S., & Alexander, T. J. (2019). GABC based neuro-fuzzy classifier with hybrid features for ECG beat classification. *Multimedia Tools and Applications, 78*(24), 35351–35372. https://doi.org/10.1007/s11042-019-08132-9

Narmatha, C., Eljack, S. M., Tuka, A. A. R. M., Manimurugan, S., & Mustafa, M. (2020). A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-020-02470-5

Neelima, G., Satish, A. R., Maram, B., & Chigurukota, D. R. (2024). CAHO-DNFN: ME-Net-based segmentation and optimized deep neuro fuzzy network for brain tumour classification with MRI. *The Imaging Science Journal, 72*(5), 557–575. https://doi.org/10.1080/13682199.2023.2211890

NGR, Hait, S. R., Guha, D., & Mahadevappa, M. (2024). Classification of epileptic EEG signals with the utilization of Bonferroni mean based fuzzy pattern tree. *Expert Systems with Applications, 239*, Article 122424. https://doi.org/10.1016/j.eswa.2023.122424

Nida, N., Irtaza, A., Javed, A., Yousaf, M. H., & Mahmood, M. T. (2019). Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering. *International Journal of Medical Informatics, 124*, 37–48. https://doi.org/10.1016/j.ijmedinf.2019.01.005

Ouchicha, C., Ammor, O., & Meknassi, M. (2023). A new approach based on exponential entropy with modified kernel fuzzy c-means clustering for MRI brain segmentation. *Evolutionary Intelligence, 16*(2), 651–665. https://doi.org/10.1007/s12065-021-00689-5

Özyurt, F., Sert, E., Avci, E., & Dogantekin, E. (2019). Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy. *Measurement, 147*, Article 106830. https://doi.org/10.1016/j.measurement.2019.07.058

Özyurt, F., Sert, E., & Avcı, D. (2020). An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine. *Medical Hypotheses, 134*, Article 109433. https://doi.org/10.1016/j.mehy.2019.109433

Padma Usha, M., Kannan, G., & Ramamoorthy, M. (2022). An efficient Berkeley's wavelet convolutional transfer learning and local binary Gabor fuzzy C-means clustering for brain tumour detection. *The Imaging Science Journal, 70*(5), 273–286. https://doi.org/10.1080/13682199.2023.2166805

Pedrycz, W., & Gomide, F. (1998). *An introduction to fuzzy sets: Analysis and design*. MIT press.

Pedrycz, W., & Sosnowski, Z. A. (2000). Designing decision trees with the use of fuzzy granulation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30*(2), 151–159. https://doi.org/10.1109/3468.833095

Prabhakar, S. K., Rajaguru, H., & Kim, S.-H. (2020). Fuzzy-inspired photoplethysmography signal classification with bio-inspired optimization for analyzing cardiovascular disorders. *Diagnostics, 10*(10), 763. https://doi.org/10.3390/diagnostics10100763

Rabcan, J., Levashenko, V., Zaitseva, E., & Kvassay, M. (2022). EEG signal classification based on fuzzy classifiers. *IEEE Transactions on Industrial Informatics, 18*(2), 757–766. https://doi.org/10.1109/TII.2021.3084352

Rabcan, J., Levashenko, V., Zaitseva, E., & Kvassay, M. (2025). Advancing ECG signal classification with a fuzzy classifier approach. *IEEE Access, 13*, 83840–83856. https://doi.org/10.1109/ACCESS.2025.3568086

Ramirez, E., Melin, P., & Prado-Arechiga, G. (2019). Hybrid model based on neural networks, type-1 and type-2 fuzzy systems for 2-lead cardiac arrhythmia classification. *Expert Systems with Applications, 126*, 295–307. https://doi.org/10.1016/j.eswa.2019.02.035

Reddy, K. R., & Dhuli, R. (2023). Detection of brain tumors from MR images using fuzzy thresholding and texture feature descriptor. *The Journal of Supercomputing, 79*(8), 9288–9319. https://doi.org/10.1007/s11227-022-05033-x

Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., Rajput, D. S., Kaluri, R., & Srivastava, G. (2020). Hybrid genetic algorithm and a fuzzy logic classifier for heart disease diagnosis. *Evolutionary Intelligence, 13*(2), 185–196. https://doi.org/10.1007/s12065-019-00327-1

Rezaie, V., & Parnianifard, A. (2022). A new intelligent system for diagnosing tumors with MR images using type-2 fuzzy neural network (T2FNN). *Multimedia Tools and Applications, 81*(2), 2333–2363. https://doi.org/10.1007/s11042-021-11221-3

Saha, S., Halder, A. K., Bandyopadhyay, S. S., Chatterjee, P., Nasipuri, M., & Basu, S. (2022). Computational modeling of human-nCoV protein-protein interaction network. *Methods, 203*, 488–497. https://doi.org/10.1016/j.ymeth.2021.12.003

Sathish, P., & Elango, N. M. (2022). Gaussian hybrid fuzzy clustering and radial basis neural network for automatic brain tumor classification in MRI images. *Evolutionary Intelligence, 15*(2), 1359–1377. https://doi.org/10.1007/s12065-020-00433-5

Sathiya, T., & Sathiyabhama, B. (2019). Fuzzy relevance vector machine based classification of lung nodules in computed tomography images. *International Journal of Imaging Systems and Technology, 29*(3), 360–373. https://doi.org/10.1002/ima.22339

Schenck, J. F. (1996). The role of magnetic susceptibility in magnetic resonance imaging: MRI magnetic compatibility of the first and second kinds. *Medical Physics, 23*(6), 815–850. https://doi.org/10.1118/1.597854

Sera, T. (2021). Computed Tomography. In K. Soga, M. Umezawa, & K. Okubo (Eds), *Transparency in Biology* (pp. 167–187). Springer Singapore. https://doi.org/10.1007/978-981-15-9627-8_8.

Sert, E., Özyurt, F., & Doğantekin, A. (2019). A new approach for brain tumor diagnosis system: Single image super resolution based maximum fuzzy entropy segmentation and convolutional neural network. *Medical Hypotheses, 133*, Article 109413. https://doi.org/10.1016/j.mehy.2019.109413

Shahbakhti, M., Beiramvand, M., Hakimi, N., Rejer, I., Lipping, T., Broniec-Wójcik, A., & Solé-Casals, J. (2024). Fusing fuzzy entropy with gaussian and exponential membership functions outperforms traditional entropy metrics in monitoring the depth of anesthesia using a single frontal EEG channel. *IEEE Sensors Letters, 8*(3), 1–4. https://doi.org/10.1109/LSENS.2024.3369318

Shalbaf, A., Saffar, M., Sleigh, J. W., & Shalbaf, R. (2018). Monitoring the depth of anesthesia using a new adaptive neurofuzzy system. *IEEE Journal of Biomedical and Health Informatics, 22*(3), 671–677. https://doi.org/10.1109/JBHI.2017.2709841

Singh, C., Ranade, S. K., Kaur, D., & Bala, A. (2024). A novel approach for brain MRI segmentation and image restoration under intensity inhomogeneity and noisy conditions. *Biomedical Signal Processing and Control, 87*, Article 105348. https://doi.org/10.1016/j.bspc.2023.105348

Siva Raja, P. M., & Rani, A. V. (2020). Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach. *Biocybernetics and Biomedical Engineering, 40*(1), 440–453. https://doi.org/10.1016/j.bbe.2020.01.006

Škrjanc, I., Iglesias, J. A., Sanchis, A., Leite, D., Lughofer, E., & Gomide, F. (2019). Evolving fuzzy and neuro-fuzzy approaches in clustering, regression, identification, and classification: A Survey. *Information Sciences, 490*, 344–368. https://doi.org/10.1016/j.ins.2019.03.060

Soares, E., Angelov, P., & Gu, X. (2020). Autonomous Learning Multiple-Model zero-order classifier for heart sound classification. *Applied Soft Computing, 94*, Article 106449. https://doi.org/10.1016/j.asoc.2020.106449

Son, L. H., Tuan, T. M., Fujita, H., Dey, N., Ashour, A. S., Ngoc, V. T. N., Anh, L. Q., & Chu, D.-T. (2018). Dental diagnosis from X-Ray images: An expert system based on fuzzy computing. *Biomedical Signal Processing and Control, 39*, 64–73. https://doi.org/10.1016/j.bspc.2017.07.005

Song, L., Liu, X., Chen, S., Liu, S., Liu, X., Muhammad, K., & Bhattacharyya, S. (2022). A deep fuzzy model for diagnosis of COVID-19 from CT images. *Applied Soft Computing, 122*, Article 108883. https://doi.org/10.1016/j.asoc.2022.108883

Tavana, M., & Hajipour, V. (2019). A practical review and taxonomy of fuzzy expert systems: Methods and applications. *Benchmarking: An International Journal, 27*(1), 81–136. https://doi.org/10.1108/BIJ-04-2019-0178

Toğaçar, M., Cömert, Z., & Ergen, B. (2021). Enhancing of dataset using DeepDream, fuzzy color image enhancement and hypercolumn techniques to detection of the Alzheimer's disease stages by deep learning model. *Neural Computing and Applications, 33*(16), 9877–9889. https://doi.org/10.1007/s00521-021-05758-5

Tugwell, P., & Tovey, D. (2021). PRISMA 2020. *Journal of Clinical Epidemiology, 134*, A5–A6. https://doi.org/10.1016/j.jclinepi.2021.04.008

Tzalavra, A. G., Andreadis, I., Dalakleidi, V. K., Constantinidis, F., Zacharaki, I. E., & Nikita, S. K. (2022). Dynamic contrast enhanced-magnetic resonance imaging radiomics combined with a hybrid adaptive neuro-fuzzy inference system-particle swarm optimization approach for breast tumour classification. *Expert Systems, 39*(4), Article e12895. https://doi.org/10.1111/exsy.12895

Vallejo, M., Gallego, C. J., Duque-Muñoz, L., & Delgado-Trejos, E. (2018). Neuromuscular disease detection by neural networks and fuzzy entropy on time-frequency analysis of electromyography signals. *Expert Systems, 35*(4), Article e12274. https://doi.org/10.1111/exsy.12274

Veronica, B. K. J. (2020). An effective neural network model for lung nodule detection in CT images with optimal fuzzy model. *Multimedia Tools and Applications, 79*(19–20), 14291–14311. https://doi.org/10.1007/s11042-020-08618-x

Versaci, M., & La Foresta, F. (2024). EEG data analysis techniques for precision removal and enhanced alzheimer's diagnosis: focusing on fuzzy and intuitionistic fuzzy logic techniques. *Signals, 5*(2), 343–381. https://doi.org/10.3390/signals5020018

Wang, C., Qian, P., Wang, Z., Cai, W., Yao, J., Jiang, Y.-Z., Yan, X., & Hu, W. (2024). Multicenter knowledge transfer calibration with rapid zeroth-order TSK fuzzy system for small sample epileptic EEG signals. *IEEE Transactions on Fuzzy Systems, 32*(11), 6224–6236. https://doi.org/10.1109/TFUZZ.2024.3443878

Wang, X., Lv, J., Kim, B.-G., Parameshachari, B. D., Li, K., Yang, D., & Shankar, A. (2025). Optimizing deep neuro-fuzzy network for ECG medical big data through integration of multiscale features. *IEEE Transactions on Fuzzy Systems, 33*(7), 2027–2037. https://doi.org/10.1109/TFUZZ.2024.3395488

Xiao, F., Liu, H., & Lu, J. (2024). A new approach based on a 1D + 2D convolutional neural network and evolving fuzzy system for the diagnosis of cardiovascular disease from heart sound signals. *Applied Acoustics, 216*, Article 109723. https://doi.org/10.1016/j.apacoust.2023.109723

Xiao, L., Zhang, S., Wu, S., Huang, H., & Hu, Z. (2025). Classification of autism spectrum disorders based on the adaptive fuzzy reasoning system. *Biomedical Signal Processing and Control, 104*, Article 107513. https://doi.org/10.1016/j.bspc.2025.107513

Yazdi, M., & Kabir, S. (2017). A fuzzy Bayesian network approach for risk analysis in process industries. *Process Safety and Environmental Protection, 111*, 507–519. https://doi.org/10.1016/j.psep.2017.08.015

Yuan, Y., & Shaw, M. J. (1995). Induction of fuzzy decision trees. *Fuzzy Sets and Systems, 69*(2), 125–139. https://doi.org/10.1016/0165-0114(94)00229-Z

Yu, H., Wu, Y., & Song, R. (2025). Investigating the Stroke- and Aging-Related changes in Intermuscular Coupling by Refined Composed Multiscale Fuzzy Entropy. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 33*, 321–331. https://doi.org/10.1109/TNSRE.2024.3502154

Zadeh, L. A. (1983). The role of fuzzy logic in the management of uncertainty in expert systems. *Fuzzy Sets and Systems, 11*(1–3), 199–227. https://doi.org/10.1016/S0165-0114(83)80081-5

Zadeh, L. A. (1992). Knowledge Representation in Fuzzy Logic. In R. R. Yager, & L. A. Zadeh (Eds.), *An Introduction to Fuzzy Logic Applications in Intelligent Systems* (pp. 1–25). US: Springer. https://doi.org/10.1007/978-1-4615-3640-6_1.

Zadeh, L. A. (2008). Is there a need for fuzzy logic? *Information Sciences, 178*(13), 2751–2779. https://doi.org/10.1016/j.ins.2008.02.012

Zaman, A., Yassin, M. M., Mehmud, I., Cao, A., Lu, J., Hassan, H., & Kang, Y. (2025). Challenges, optimization strategies, and future horizons of advanced deep learning approaches for brain lesion segmentation. *Methods, 239*, 140–168. https://doi.org/10.1016/j.ymeth.2025.04.016

Zhou, K., Oh, S.-K., Qiu, J., Pedrycz, W., Seo, K., & Yoon, J. H. (2024). Design of hierarchical neural networks using deep LSTM and Self-organizing dynamical fuzzy-neural network architecture. *IEEE Transactions on Fuzzy Systems, 32*(5), 2915–2929. https://doi.org/10.1109/TFUZZ.2024.3361856