Research Article

Fuzzy Inference Techniques in Medical Diagnosis: Bibliometric Analysis and a Systematic Literature Review

Rajat Kapoor[1*], S. S. Bedi[2],Yash Pal Singh[3]
[1]Research Scholar,CSITDepartment,MJPRU,Bareilly(U.P.),India
EMAILID: merajatkapoor@gmail.com
[2]Professor,CSIT Department, MJPRU,Bareilly(U.P.),India
EMAILID :ssbedi@mjpru.ac.in
[3]Sr. Scientist,ARIS Cell, IVRI Izatnagar,Bareilly(U.P.),India
EMAILID: yash@ivri.res.in

Abstract
The Fuzzy Inference Systems (FIS) have proven to be an important tool in the imprecision and relevant manipulation indeterminacy, especially in the field of medical diagnosis where humans are able to think discretionally decision-making is necessary. The increase in health care data and the necessity of explainable AI have increased the interest of researchers in creation and advancement of fuzzy inference techniques. There is a growing interest among scholars in inference models of various kinds the knowledge of the most essential factors that predetermine the choice of the best inferencing mechanisms. Here, the current paper examines the intellectual organization and history of development of research fuzzy inference systems with particular focus on their medical diagnosis applications. The experimentally analyzes central thematic domains, increasing publication, referencing tendencies, top publication sources, major contributors, and keywords that keep on reoccurring in this area. It further identifies the gaps in research at hand and describes the future directions of the research exploration. The approach that this study takes in a methodological sense is a dual one; it is a combination of Systematic. Bibliometric analysis and Literature Review (SLR). There are 619 research articles contained in the dataset databases, such as ScienceDirect, are the major source of information, and the choice of entries is made based on their relevance scholarly literature, dating back to 2000-2025. The outcomes are informative into the current research focus and intellectual premises which have informed the fuzzy inference in medical diagnosis.

Keywords: Fuzzy Inference Systems (FIS), uncertainty, decision-making, fuzzy inference techniques, AI, medical diagnosis, Systematic Literature Review (SLR), Bibliometric analysis
How to cite this article: Kapoor R, Bedi SS, Singh YP, Fuzzy Inference Techniques in Medical Diagnosis: Bibliometric Analysis and a Systematic Literature Review. Int J Drug Deliv Technol. 2026;16(4s): 344-365; DOI: 10.25258/ijddt.16.4s.45

1. Introduction

The use of computational intelligence in medical diagnostics has increased significantly over the past 2 decades, both as a result of the complexity of the data, the necessity of offering clinical decision support in a timely manner, and the wish to concentrate on interpretable artificial intelligence. Fuzzy inference system among other computational methods have become a cornerstone in modeling uncertainty, as a method of approximating human reasoning, and a tool in dealing with uncertain or incomplete clinical data. Based on a larger theory of fuzzy logic and fuzzy sets proposed by Zadeh [1], fuzzy inference models allow explicit conversion of qualitative medical knowledge into computational models based on rules. In contrast to classical binary logic, fuzzy logic can handle the truths of the range 0 to 1 [2], whereas the fuzzy set theory gives membership values that measure vagueness and imprecision of the real-world data [3]. The field of fuzzy logic began to gain significant interest after 1991 and its share in the number of publications devoted to fuzzy logic rose to about 40 percent [4]. This wave can be associated with the growing demands of smart systems that can be used in the setting with ambiguity, i.e., disease identification, patient monitoring, and risk assessment. Healthcare environments today often deal with complicated, nonlinear connections between symptoms, laboratory results, and patient histories, and in these cases, crisp, rule-based or purely statistical methods may not suffice. In addition to the classical models of fuzzy reasoning, modern developments have also brought on board neuro-fuzzy systems, hybrid fuzzy-machine learning systems and deep fuzzy systems that provide better predictive capabilities and still have the ability to be interpretable [5]. These advancements are indicative of a strategic change that is towards open AI, in response to the increasing requirements of clinical systems the outputs of which are explainable and justifiable.[6] It is against this background that there is an urgent need to evaluate systematically the way research in this field has developed, which are the most effective techniques, and what theme is predominant among scholars nowadays. This paper fulfills such demands by using a mixed methodology of bibliometric review and systematic review on a collection of 619 publications between 2000 and 2025 [7]. In particular, it examines the dynamics of the growth of publications, the authors and journals with the highest influence, topical groups, preference in methodology and developing hybrid systems[8]. The following seven research questions help the study to focus on understanding publication evolution, influence of contributors, journal prominence, the relationships between keywords and research clusters, key inference methods, and the opportunities in future research, especially the way to evolve the method, the applications, and the integration across different disciplines [9].The research questions will help inform the researchers, practitioners, and policymakers about the current achievements and what type of research can be conducted in the future[10]. It is aimed at assisting new and seasoned researchers in exploring the challenging yet prospective landscape of fuzzy inference in healthcare analytics [11].

2. Methodology

The research design adopted in the paper is a dual research design consisting of a Systematic Literature Review (SLR) and Bibliometric Analysis that presents a multidimensional and intricate view of the fuzzy inference methods particularly when used in medical diagnosis. The bibliometric analysis database utilized in the given study consisted of 619 articles found through primarily the ScienceDirect database and the remaining useful articles were located through PubMed, Scopus, IEEE Xplore and Wiley among other reliable databases [12]. To ensure the recency and relevance of the information gotten, the search was limited to the years 2000 to 2025. The search was based on the most popular fuzzy inference models and their use in the area of diagnostics, and the query: ((Mamdani) OR (Sugeno) OR (Tsukamoto) AND (Disease Diagnosis) OR (Medical Diagnosis)).

All the retrieved records were then subjected to a multi-stage screening. Articles were first filtered to eliminate duplicates and those in not English before filtering out encyclopedia articles, editorial articles, case reports, conference abstracts (without full text), brief communications, announcement of software and articles outside the field of fuzzy inference or medical diagnosis. In accordance with the use of these criteria, 619 documents were retained in order to be subjected to bibliometric research. The samples were collected in the case of the SLR through the rigorous full-text evaluation that ensured that every article contains a clear description of the methodology of the fuzzy inference technique used including the type of membership functions, diagnostic field, and other performance indicators such as accuracy or system reliability[13]. The SLR was conducted in a systematic process, whereby the relevant literature was identified, preliminarily in terms of title and contents of abstract, preliminarily in terms of full-text eligibility and exclusion of ineligible papers. The chosen studies were all assessed to find out the information on the inference model applied (Mamdani, Sugeno or Tsukamoto), nature of the membership functions, nature of the disease, the nature of the data and the aim of the systems and the accuracy of the diagnosis.

3. Software and Method of Analysis

The current analysis follows a two-fold analytical model of a Systematic Literature Review (SLR) and a bibliometric analysis that offers an overall view of medical diagnosis based on fuzzy inference methodologies. The SLR approach is generally known in terms of methodological rigour, transparency and the synthesis of existing knowledge in a systematic manner. In contrast to narrative reviews, SLRs have a systematic literature identification, screening and evaluation process thus guaranteeing reliability and reproducibility of findings [14], [15], [16].

3.1 Systematic Literature Review Procedure

The SLR process was initiated with the identification of the relevant studies on the basis of the predefined search strings that involved the most popular fuzzy inference models including Mamdani, Sugeno and Tsukamoto, mixed with the medical diagnosis terms. To be able to cover the domain as much as possible, several academic databases such as ScienceDirect, PubMed, Scopus, IEEE Xplore and Wiley Online Library were researched. Peer-reviewed articles published within 2000-2025 were used to limit the search to modern developments in the field of fuzzy logic, as well as its use in diagnosing problems.

Following the retrieval of the preliminary dataset, the duplicates of the data were eliminated and the process of screening titles, abstracts and full texts was implemented in multi-stages. Publications in non-English languages not writing about the medical field, entries in the encyclopedia, brief messages, papers that lacked clarity in the methodology, research that was not relevant to fuzzy inference were excluded. This intensive screening procedure lead to 13 major studies which fit the inclusion criteria. In each of the chosen studies a data extraction was performed in detail, the fuzzy inference technique applied, the nature of the membership functions, the area of the diagnostic task, the nature of the data set and the performance measures, say the accuracy or the reliability.

3.2 Bibliometric Analysis Tools and Workflow

In order to supplement the SLR results with macro-level scientific trends, bibliometric analysis was carried out on a sample of 619 articles. Bibliometrical technique makes it possible to statistically analyze knowledge structures, research evolution, and publication with the help of scientific literature dynamics across domains [17]. The bibliometrix R package with its graphical interface Biblioshiny, both of which are well-known science mapping, cooccurrence network and citation analysis tools were used to conduct the analysis [18], [19].

The bibliometric process encompassed:

- **Annual scientific production analysis**, highlighting temporal research patterns.
- **Authorship productivity and collaboration network mapping**, identifying influential contributors.
- **Source impact assessment** using h-index, g-index, and m-index to determine journal influence.
- **Keyword co-occurrence and cluster analysis**, revealing dominant themes and emerging research directions.
- **Citation analysis**, identifying highly influential publications, authors, and conceptual frameworks.

Social network metrics—such as Betweenness, Closeness, and PageRank centrality—were computed to determine the relative influence of authors, keywords, and thematic clusters within the research network.

3.3 Integrated Analytical Approach

The combination of SLR and bibliometric methods allowed furnishing both micro-level information about fuzzy intelligible approach to inference and macro-level knowledge of publication tendencies, intellectual nations and evolutionary development of the discipline [20]. Whereas in-depth analysis was possible with the SLR of the abilities of single models to diagnose (e.g., Mamdani, Sugeno, Tsukamoto). These methods were contextualized in terms of scientific developments more broadly through bibliometric analysis,underlining research clusters, structural changes and developing hybrid practices [21].

4. Findings and Discussion

This section presents the outcomes of the bibliometric analysis conducted on the selected body of literature spanning from 2000 to 2025. The findings highlight the growing scholarly attention toward fuzzy inference systems (FIS) in the field of medical and disease diagnosis, showcasing trends in publication volume, citations metrics, most productive journals , active contributors, keyword frequency, and co-occurrence patterns.

4.1. Annual Scientific Production: Trends and Growth in Fuzzy Inference Techniques Research

The study of Fuzzy Inference Techniques has quietly but progressively gained momentum over the last 25 years. In the early 2000s, research activity was fairly limited, with only a few papers appearing each year. Significant growth was in subsequent years reaching a peak of 69 publications in 2023 (Figure 1).

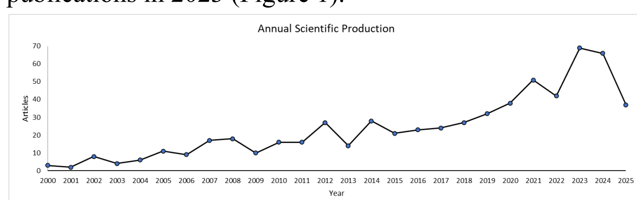

Figure 1: Annual Scientific Production of Fuzzy Inference System (2000-2025)

Table 1 shows the quantitative summary of research articles highlighting average articles/year and most productive year. An average annual growth rate can be estimated from early (2000s) to peak (2023) as roughly >10% annually, especially from 2014 onward. An examination of the annual publication data from 2000 to 2024 reveals a clear upward trajectory in research activity related to Fuzzy Inference Techniques.

***Table 1**: Quantitative summary of Annual Scientific Production in Fuzzy Inference Techniques Research (2000–2025)*

Metric	Value

Total Articles	620
Average Articles/Year	~29.0
Most Productive Year	2023 (69 articles)
Growth Period	2000–2025 (26 years)

To analyze the trend, we have considered five periods to divide the growth period. Figure 1 highlights five different stages: Initial (2000-2006), Growth (2007-2014), Consolidation (2015-2020), Accelerated Growth (2021-2023) and Recent Plateau or Adjustment (2024-2025).

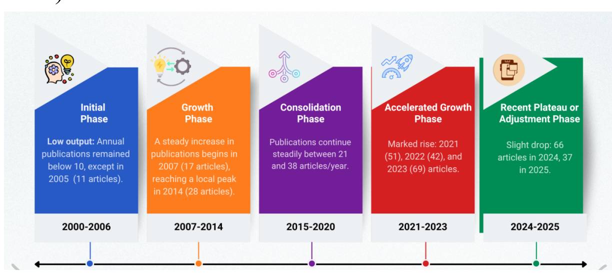

Figure 2: Phase-wise Growth in Scientific Publications on Fuzzy Inference Techniques

Initial Phase indicates the early phase of research of fuzzy inference technique in the mainstream literature. Growth Phase implies the increase in interest and usage of fuzzy logic in the disciplines similar to AI, control systems and data analysis. Consolidation Phase implies stable academic perhaps because of its use in intelligent systems with uncertainty. Accelerated Growth Phase indicates mass hype on fuzzy inference because of the surge in its application in Artificial intelligence/machine learning, medicine and robotics. New Plateau or Adjustment phase the number of publications is less might be because of unfinished indexing.

The chart (Figure 3) represents the phased development of the scientific publications about fuzzy inference methods of 2000 to 2025 and this is divided into five different research phases. Each

phase is represented by colors that indicate changes in the trends of publication with time.

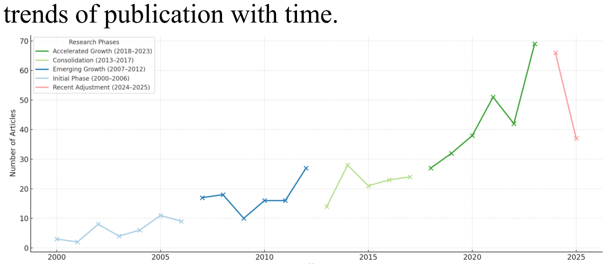

Figure 3: Phase-wise growth in Scientific Publications on Fuzzy Inference Techniques (2000-2025)

The research in fuzzy inference has gained momentum particularly in the last 5 years. 2023 is the peak year with 69 publications, showing a significant spike. A noticeable growth trend starts from 2007 and gains real momentum post-2014. Possible factors driving growth are integration of fuzzy logic with AI and deep learning, Increase in real-world applications needing uncertain or imprecise reasoning and enhanced computational power and tools supporting fuzzy systems[22].

4.2. Average Citations per Year (Trends in Average Citations to Fuzzy Inference Techniques)

Figure 4 shows the analysis of average citations per year of the studies on Fuzzy Inference Techniques shows an uneven distribution, where some years are more emphasized since of the publications that are highly cited. It is important to note that, in the years 2004, 2012, 2017, 2022 and 2024, the citation spikes are observed to have an average citation rates of 15.18, 15.97, 9.56, 24.25, and 30.65 respectively. These mountains indicate that within these there were seminal influential papers which were published in specific years attracting much scholarly interest over time. Other years, especially 20052011, and 20182021 reveal many other years, however, with increased numbers of cases little or no increase in citation, meaning that there was a lack of publications in those times scholar influence or have yet to reach the stage of citation accretion.

Interestingly, there have been encouraging average citation trends in the recent years such as 2023 and 2024,which can be attributed to the increased applicability and use of fuzzy inference methods in new AI, machine learning, and intelligent decision systems are all technologies. On the other hand,the last year 2025, has no average citation, as expected by the reason of the reason that they are of recent date.

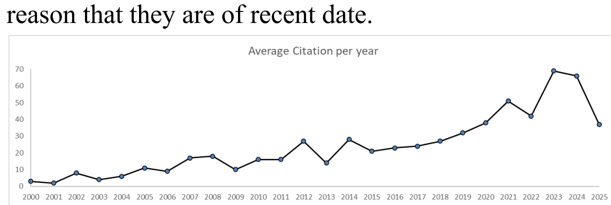

Figure 4: Average citations per year for studies on Fuzzy Inference Techniques

4.3. Most Relevant Sources (Leading Journals in Fuzzy Inference)

The table 2 provides the Leading Journals in Fuzzy Inference Techniques with 4 or above publications. On closer inspection of the journal-wise frequency of publication, one will find that there is a high degree of concentration publication of academic work in a small number of specialized journals, which highlights the background value such journals can bring regarding the spread of the research on fuzzy inference systems.The first one is Expert Systems with Applications topping it with 78 articles. It demonstrates that this journal is extremely doing publications in the field of fuzzy logic. Then there is Applied Soft Computing which has 45 the next big players are articles then Information Sciences with 42 articles this field. Engineering Applications of Artificial Intelligence are some of the other important sources. The articles employed a range of diverse methods.The number of different methods used in the articles was high articles. These journals demonstrate that fuzzy inference is finding application in several areas such as artificial intelligence, healthcare and engineering. A noteworthy trend is the emergence of domain-specific journals—such as Biomedical Signal Processing and Control, Neurocomputing, and Computers in Biology and Medicine—which collectively suggest a growing interest in embedding fuzzy models within biomedical contexts. These outlets demonstrate how fuzzy inference is being adopted to navigate complex, uncertain, and noisy environments often encountered in clinical data and physiological modeling [23], [24]. The long tail of journals with 4–6 publications each, such as Information Fusion, Pattern Recognition, Computers and Electronics in Agriculture, and Digital Signal Processing, illustrates the broad and interdisciplinary diffusion of fuzzy inference techniques [25]. This speaks to the technique's adaptability and growing traction in highly specialized niches.

Table 2: M*ost relevant academic sources in fuzzy inference research based on publication frequency (4 or more).*

Rank	**Source Title**	**Articles Published**
1	Expert Systems with Applications	78
2	Applied Soft Computing	45
3	Information Sciences	42
4	Engineering Applications of Artificial Intelligence	24
5	Fuzzy Sets and Systems	23
6	Artificial Intelligence in Medicine	20
7	Biomedical Signal Processing and Control	17
8	Neurocomputing	14
9	Knowledge-Based Systems	12
10	Computers in Biology and Medicine	11
11	Procedia Computer Science	9
12	Heliyon	8
13	COMPUTERS, MATERIALS AND CONTINUA	7
14	INTERNATIONAL JOURNAL OF APPROXIMATE REASONING	7
15	BIOCYBERNETICS AND BIOMEDICAL ENGINEERING	6
16	COMPUTER METHODS AND PROGRAMS IN BIOMEDICINE	6
17	INFORMATICS IN MEDICINE UNLOCKED	6
18	INFORMATION FUSION	6
19	JOURNAL OF BIOMEDICAL INFORMATICS	6
20	JOURNAL OF KING SAUD UNIVERSITY - COMPUTER AND INFORMATION SCIENCES	6
21	DIGITAL SIGNAL PROCESSING	5
22	MEASUREMENT	5
23	COMPUTERS AND ELECTRONICS IN AGRICULTURE	4

24	IFAC-PAPERSONLINE	4
25	PATTERN RECOGNITION	4

As it can be seen in chart (Figure 5) the top 5 journals in itself represent more than 45% of the total articles, which means that there is a high degree of concentration in terms of publication sources. The prevalence of medical and biomedical journals is an indication of a paradigm shift: the fuzzy logic as the control tool is replaced by fuzzy logic as the part of human domain. Fuzzy inference methods have a multidisciplinary character, and the wide range of journals, including computer science and agriculture, indicates its growing use in real-world situations.

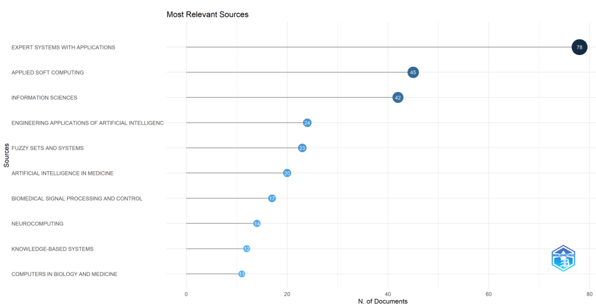

Figure 5: Leading Journals contributing to research on Fuzzy Inference Techniques

4.4. Top Contributing Journals

There are journals that have contributed significantly in the sphere of fuzzy inference, which can be measured by citation impact and productivity (Table 3). It is evident that "Procedia Computer Science" has the best h-index of 6, 6140 total citations, and 9 publications since 2011. Although it has less papers, its influence is high. The impact of "Materials Today: Proceedings" is also good with 4044 citations in only 2 papers indicating very high average citations per paper[26]. Journals such as Fuzzy Sets and Systems and Neurocomputing demonstrate great influence by having g-index values of 14 and 14 respectively which implies that there are highly cited papers. Interestingly, other journals like "IFAC-PapersOnline" and International Journal of Approximate Reasoning record balanced outcomes, both in terms of decent citations and good m-index. Journals that have m-index sharply above 0.4 such as "IFAC-PapersOnline" (0.8), "Materials Today: Proceedings" (0.5) and "Procedia Computer Science" (0.4) indicate that they have steady impact as compared to their age of publication. This data is also represented in Figure 6 that indicates sources local impact by h-Index.

Table 3: *Top Journals by Source Impact (Based on h-index, g-index, m-index)*

Journal Name	**h-index**	**g-index**	**m-index**	**Total Citations (TC)**	**No. of Papers (NP)**	**Since**
PROCEDIA COMPUTER SCIENCE	6	9	0.4	6140	9	2011
IFAC-PAPERSONLINE	4	4	0.8	64	4	2021
IFAC PROCEEDINGS VOLUMES	3	3	0.2	48	3	2011
INTERNATIONAL JOURNAL OF APPROXIMATE REASONING	2	7	0.105	58	7	2007
MATERIALS TODAY: PROCEEDINGS	2	2	0.5	4044	2	2022
COMPUTERIZED MEDICAL IMAGING AND GRAPHICS	1	14	0.048	219	23	2005
COMPUTERS & CHEMICAL ENGINEERING	1	14	0.045	2004	14	2004
ENERGY PROCEDIA	1	5	0.042	25	12	2002

FUZZY SETS AND SYSTEMS	1	3	0.0 43	20	3	20 03
KNOWLEDGE-BASED SYSTEMS	1	1	0.0 71	2011	1	20 12
NEUROCOMP UTING	1	14	0.0 48	219	23	20 05
PHYSICA C: SUPERCONDU CTIVITY	1	5	0.0 42	25	12	20 02

Analysis clearly shows that Procedia Computer Science has the biggest impact and Materials Today has very few papers but very high citations. Fuzzy Sets and Systems and Neurocomputing have papers that are highly cited. IFAC-PapersOnline has good recent performance. Some journals are very new but already showing strong results (started after 2020).

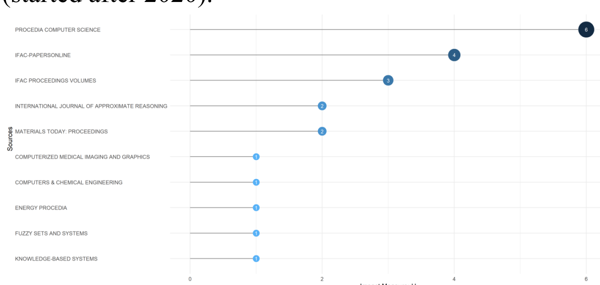

Figure 6: Sources' Local Impact by h-index

4.5. Trending Journals: Yearly Production Overview

To find the trendy journal, we analyzed Figure 7 and found that among all, Expert Systems with Applications is growing the fastest and has the highest output. It shows consistent growth, especially after 2010. Applied Soft Computing started late but is growing quickly. It picked up pace after 2014, information Sciences has grown steadily and crossed 40 papers in 2025. Engineering Applications of AI grew slowly at first, but saw big jumps after 2020. Fuzzy Sets and Systems shows stable but moderate growth, becoming more active in recent years.

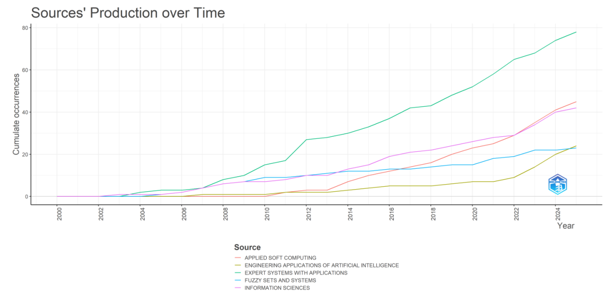

Figure 7: Growth of Journals over time

4.6. Leading authors working on Fuzzy Inference techniques

Table 4 demonstrates the top 20 contributing authors in Fuzzy Inference System and it shows that FRANCISCO HERRERA is the top contributing author with 9 publications followed by JOÃO M.C. SOUSA and SUSANA M. VIEIRA with 7 publications each. AJAY KUMAR, MAMTA DAHIYA, RAHUL BOADH and YOGENDRA KUMAR RAJORIA have highest citation of 4044. These authors share exactly 4044 citations and started in 2022, suggesting co-authorship on a highly cited publication.

Figure 8 visualizes the descriptive analysis of h-index , d-index and m-index reported for 98 authors. There are 8 authors with 2 h-index. 6 authors(FRANCISCO HERRERA, JOÃO M.C. SOUSA, SUSANA M. VIEIRA, HOSSEIN AHMADI, MEHRBAKHSH NILASHI ,STAN FINKELSTEIN, ARKADIUSZ GERTYCH) have slightly higher g-index (>=4). Many recent authors(Year 2022-2024) have highest m-index(0.5). JOÃO M.C. SOUSA & SUSANA M. VIEIRA were steady contributors since 2010 with relatively high g-index.

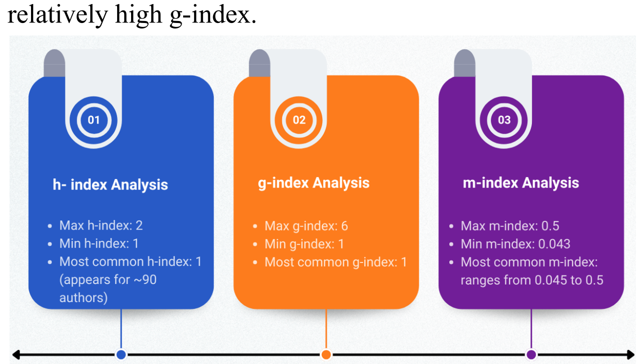

Figure 8: Descriptive analysis of h-index, g-index and m-index

Table 4: *Leading Authors working on Fuzzy Inference System*

Author	h_index	g_index	m_index	TC	NP	PY_start
FRANCISCO HERRERA	1	5	0.071	25	9	2012
JOÃO M.C. SOUSA	2	6	0.125	36	7	2010
SUSANA M. VIEIRA	2	6	0.125	36	7	2010
HOSSEIN AHMADI	1	4	0.111	26	4	2017
MEHRBAKHSH NILASHI	1	4	0.111	26	4	2017
STAN FINKELSTEIN	1	4	0.067	18	4	2011
ARKADIUSZ GERTYCH	1	3	0.043	20	3	2003
LEILA SHAHMORADI	1	3	0.111	26	3	2017
AJAY KUMAR	2	2	0.5	4044	2	2022
HIMANSHU KUMAR R. PATEL	2	2	0.5	31	2	2022
MAMTA DAHIYA	2	2	0.5	4044	2	2022
RAHUL BOADH	2	2	0.5	4044	2	2022
VIPUL A. SHAH	2	2	0.5	31	2	2022
YOGENDRA KUMAR RAJORIA	2	2	0.5	4044	2	2022
ABIGAIL L. HORN	1	2	0.067	18	2	2011
ANDRÉ S. FIALHO	1	2	0.067	18	2	2011
BAYRAM AKDEMIR	1	2	0.056	2011	2	2008
EWA PIETKA	1	2	0.043	20	2	2003
FEDERICO CISMONDI	1	2	0.067	18	2	2011
HAMIDO FUJITA	1	1	0.083	2	2	2014
NP= Number of Publications, TC= Total Citations, PY_Start= Publication Year Start						

Many Indian researchers submitted their publications in year 2022 and year 2023–2024 have seen numerous emerging contributors. Many authors with 1 publication and m-index of 0.5 started in 2023 or 2024 that indicates recent impactful work. Several authors have identical metric sets (e.g., h=1, g=1, m=0.071, TC=2012, PY=2012) that could be possibly co-authors on the same paper.

Figure 9 shows highly producing authors on Fuzzy Inference Techniques over time. Oscar Castillo has shown consistent annual output from 2009 to 2022, often collaborating with Patricia Melin. Their joint work on hybrid intelligent systems, interval type-2 fuzzy systems, and medical applications makes them long-standing contributors. Francisco Herrera had a strong early presence, peaking between 2012 and 2022 with highly cited works in evolutionary fuzzy systems, handling imbalanced datasets, and soft computing [27]. Patricia Melin and Oscar Castillo emerges as the longest consistently active author in this domain, with a publishing span of 13 years and continuous annual contributions.

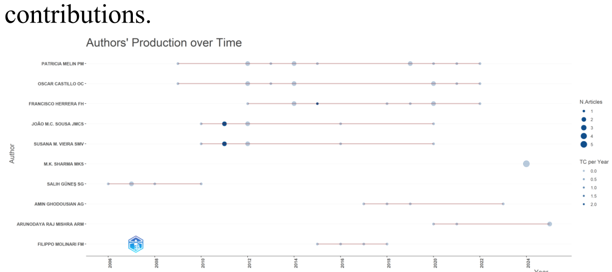

Figure 9: Top Author's production over time

4.7. Most Relevant Keywords

The frequency distribution of keywords in the collected corpus offers deep insights into the thematic core and interdisciplinary breadth of research on fuzzy inference techniques. Figure 10 shows the frequency of top 20 most frequent words and word cloud (Figure 11) shows the relevant words used in this domain. As can be seen at the forefronts are foundational terms such as Fuzzy Sets and Fuzzy Logic, registering 79 and 74 mentions respectively. These terms serve as the conceptual backbone of the literature and confirm the field's enduring reliance on classical fuzzy theory. Further various extensions and modifications to fuzzy sets like shadowed fuzzy set [28], quintic fuzzy set [9], quartic fuzzy sets [29], lattice valued fuzzy sets [30], hesitant fuzzy set [31], fermatean fuzzy set [32], eigen fuzzy set [33], disc spherical fuzzy sets[[33], complex fuzzy set [34], bipolar intuitionistic fuzzy set [34], pythagorean fuzzy set [35], interval type-2 fuzzy sets [36], picture fuzzy sets [37], type-2 fuzzy set[38] and intuitionistic fuzzy[39] set were explored; each designed to handle different aspects of uncertainty and vagueness.

The prevalence of such terms as Diagnosis (50), Classification (45), and Expert System (36) is very high, which implies that the most common way of applying fuzzy inference is in the context of decision support, specifically in healthcare, fault detection, and intelligent automation systems. These applications take advantage of the ability of fuzzy logic to deal with uncertainty and imprecision, which simple diagnostic tasks in the real world have. New concepts can be seen in the prevalence of Machine Learning (48), Deep Learning (29), and Artificial intelligence (27) as the paradigm of fuzzy logic intersects with the current trends of AI. It was observed in contemporary models like neuro-fuzzy systems and deep fuzzy networks, where the explicatory nature of fuzzy logic balances the data-mining prowess of neural networks.

Ideas like Feature Selection (16) and Interpretability (15) also underline the increased interest in making intelligent systems more transparent and more focused on performance, particularly in high-stakes settings where models have to be able to justify their choices. Classical models of fuzzy inference, including Mamdani (6), Sugeno (5), and Tsukamoto (12), are present with median frequency, meaning that these models are not so much reformulated, but the larger number of applications of fuzzy inference is emerging. Likewise, Fuzzy Control, Pattern Recognition and Fuzzy Clustering emphasize the variety of the method in control systems, signal processing, and unsupervised learning.

The repeated reference to Uncertainty (10) emphasizes the niche placement of fuzzy logic in representation of vague, incomplete, or subjective data, and serves to support its superiority over binary logic and statistical modeling in some situations.

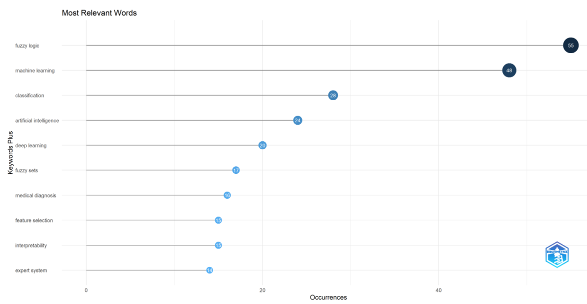

Figure 10: Frequency of 20 Most relevant words

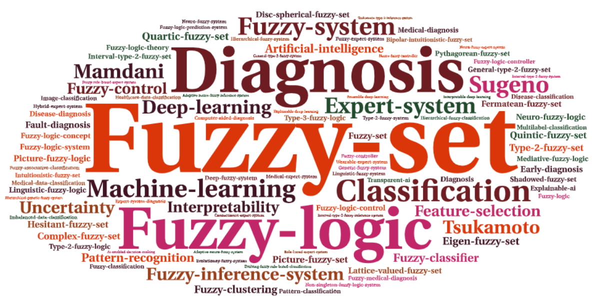

Figure 11: Word cloud depicting top most relevant words

4.8. Keyword Co-occurrence Analysis

The co-occurrence analysis key word yields a useful information on the main ideas and connections within the sphere of Fuzzy Inference Techniques. The centrality measures based on PageRank, Betweenness and Closeness have been used to analyze keywords (Table 5) and cluster assignments have been used to identify thematic groupings.

Table 5: *Keyword co-occurrence table showing 9 clusters*

Node	Cluster	Betweenness	Closeness	PageRank
classification	1	287.956	0.014	0.085
feature selection	1	0	0.01	0.012

interpretability	1	40.124	0.01	0.03
anfis	1	0.878	0.009	0.012
fuzzy systems	1	0	0.009	0.012
clustering	1	7.725	0.01	0.025
explainable artificial intelligence	1	0	0.007	0.01
decision tree	1	0	0.009	0.01
entropy	1	9.405	0.01	0.016
similarity measure	2	40.455	0.008	0.036
pattern recognition	2	126.845	0.01	0.036
fuzzy set	2	0	0.006	0.013
intuitionistic fuzzy set	2	38	0.008	0.027
intuitionistic fuzzy sets	2	0	0.006	0.01
machine learning	3	155.327	0.013	0.086
artificial intelligence	3	113.167	0.013	0.056
deep learning	3	38	0.01	0.031
neural networks	3	33.589	0.012	0.029
data mining	3	0	0.01	0.018
artificial neural network	3	2.836	0.009	0.015
support vector machine	3	9.103	0.01	0.019
covid-19	3	0	0.007	0.008
internet of things	3	0	0.008	0.01
fuzzy logic	4	373.928	0.014	0.105
expert system	4	0	0.009	0.017
breast cancer	4	1.5	0.01	0.019
diagnosis	4	0	0.009	0.008
fuzzy inference system	4	0	0.009	0.008
computer-aided diagnosis	4	0	0.009	0.014
decision support systems	4	0	0.009	0.008
fuzzy clustering	5	38	0.009	0.02
fuzzy classifier	5	0	0.007	0.014
feature extraction	6	38	0.01	0.021
computer aided diagnosis	6	0	0.007	0.009
genetic algorithm	7	76.246	0.01	0.036
neural network	7	0	0.007	0.009
optimization	7	0	0.007	0.012
medical diagnosis	8	16.161	0.009	0.02
uncertainty	8	1	0.007	0.015

disease diagnosis	8	21.757	0.009	0.015
fuzzy sets	9	0	1	0.024
expert systems	9	0	1	0.024

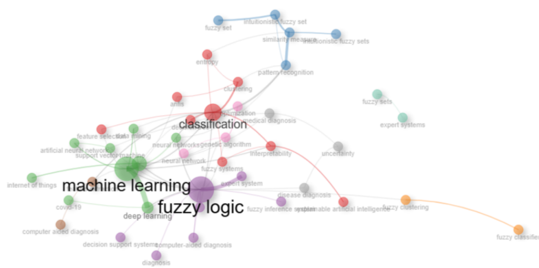

Figure 12*; shows that 'Fuzzy Logic' and 'Machine Learning' has emerged as a significant topic and has attracted the interest of researchers.*

Dominating Themes and Nodes: The keyword, Fuzzy Logic, recorded the highest PageRank (0.105) and highest Betweenness centrality (373.928) and this confirms its centrality in several domains that the study of fuzzy inference systems encompasses. It has a high Closeness value (0.014), implying that it is directly linked to a large number of other words and is a central node in the network. This means that not only is fuzzy logic widespread, but also it is at the heart of the development of methodology in research clusters. On the same note, such integrative words as "Machine Learning" (PageRank: 0.086) and "Classification" (PageRank: 0.085) were also discovered, which is the transition between the old fuzzy systems and the new AI paradigm. The significance of them in the network suggests that fuzzy systems and intelligent data-driven methods are becoming closely related to one another in modeling, classification and in supporting decisions.

Cluster-Level Insights

- **Cluster 1** includes keywords like classification, feature selection, interpretability, and clustering, indicating that it is centered on explainable fuzzy models and decision-making architectures. The high score in interpretability (Betweenness: 40.124) highlights the increased focus on transparent and accountable AI.
- **Cluster 3** focuses on machine learning, deep learning, neural networks, and support vector machines, which implies the inclusion of fuzzy inference in hybrid artificial intelligence models.
- **Cluster 4** contains diagnosis, expert system, fuzzy inference system, and decision support systems with a focus on medical and clinical applications, in particular, in computer-aided diagnosis and predicting diseases.
- **Cluster 7**, in which genetic algorithm has high Betweenness (76.246) indicates an interest in the optimization techniques of fuzzy systems.

Emerging Areas of Interest: The appearance of such terms as explainable artificial intelligence, COVID-19, and Internet of Things (Cluster 3) indicate the extension of the fuzzy logic applications to the modern real-life situations. Their lower centrality scores do not mean that they do not present emergent research interests, even though they are included. The fact that fuzzy sets and expert systems are clustered in Cluster 9 and have a perfect value of Closeness (1.0) indicates that they have constrained foundational topics that are universally referenced in the clusters, but are less bridging. The terms of Artificial Intelligence, Deep Learning are among the keywords related to modern Fuzzy Inference Systems, which can be regarded as the transition to more developed, more adaptive systems in such fields as pattern recognition and classification. Artificial Intelligence (0.056) and Deep Learning (0.031) have high PageRank scores, which means that they are increasingly relevant in the sphere. Intuitionistic Fuzzy Sets and Fuzzy Clustering are also promising with a greater centrality in the research network (40.455 and 38, respectively), indicating their significance in uncertainty management and offering useful way of clustering.

Specialized Topics: Expert Systems and Decision Support Systems continue to be areas of interest within the context of the application of Fuzzy Inference to real-world applications, including diagnosis (e.g., breast cancer, medical diagnosis), which notes the increasing involvement of optimization solutions with fuzzy systems to refine solutions to complex decision-making processes.Genetic Algorithm and Optimization are terms that signify the ever-increasing incorporation of optimization solutions in conjunction with fuzzy systems to help optimize the solutions in complex decision-making.

Domain-Specific Applications : Medical Diagnosis and Disease Diagnosis: Two notable examples are domain-specific applications where Fuzzy Logic is significant to find solutions to uncertainty and imprecision in diagnostic systems. Such keywords, together with the computer-aided diagnosis and breast cancer, indicate a narrowed research focus which tends to advance the field of health informatics via fuzzy logic-based system.

Interconnectivity and Bridging Concepts: The cluster bridging concepts include pattern recognition (Betweenness: 126.845) and artificial intelligence (Betweenness: 113.167), which enable the transfer of knowledge between thematic clusters. These are probably the keywords that can bridge methodological and application-oriented research [40], [41], [42].

4.9. Future Research Directions using co-occurrence of keywords

The outcomes of the key-word co-occurrence and bibliometric analysis indicate that there are a number of emergent themes and gaps in the research of the topic of fuzzy inference systems. The following research directions are proposed based on the clustering of high-betweenness and high-pagerank keywords that include classification, machine learning, fuzzy logic, and interpretability.

Incorporation and combination of Explainable Artificial Intelligence (XAI) and Fuzzy Systems:

As the need to have more model transparency and accountability grows, the intersection between fuzzy systems and explainable artificial intelligence is a promising area of research. It has been indicated that the close co-occurrence of words like interpretability, explainable AI and fuzzy systems implies that there is a need to develop models that are not only precise but also comprehensible to human beings. Future studies ought to tackle the development of interpretable fuzzy inference architecture to be used in the context of applications where the decision traceability is paramount, e.g., healthcare, finance, and legal analytics.

Hybrid Neuro-Fuzzy Models: The development of deep learning, neural networks, and machine learning in close relation to fuzzy inference systems and fuzzy classifiers is an indication of increased demands in hybrid intelligent systems. The potential of deep neuro-fuzzy models that combine the pattern learning capacity of deep networks with approximate reasoning of the fuzzy logic can be discussed in the future. Unstructured data settings such as image and speech recognition, natural language processing, and time-series forecasting may be useful in such models.

Medical Diagnosis and Decision Support Systems: Medical diagnosis, disease diagnosis, computer-aided diagnosis, and breast cancer are key words to reveal that the use of fuzzy systems in healthcare is increasing in the number of applications. It can be developed that there are opportunities to develop strong diagnostic assistance systems that process imprecise, noisy, or incomplete data with the aid of fuzzy logic. Scholars can pay attention to the combination of real-time patient information and fuzzy expert systems to detect danger in advance, prognose, and recommend individual treatment.

Optimization-Based Fuzzy Systems: The addition of genetic algorithms and optimization as well as fuzzy-related terminology hint at the fact that fuzzy rule basis and membership functions will also require optimization. Future studies can focus on multi-objective optimization based on metaheuristics, e.g. genetic algorithms, particle swarm optimization, or ant colony optimization that can allow optimization of fuzzy inference parameters. Such techniques have the potential to improve the stability and flexibility of fuzzy models in dynamic system control and control.

The use of Fuzzy Logic in Smart and Sustainable Systems: The very keyword Internet of Things (IoT) and associated terms are signs of increasing applicability of smart technologies. Scientists can come up with fuzzy logic decision model of IoT-based systems, smart grids, and smart agriculture to handle ambiguity sensor data. Such applications require energy efficient, scalable, and context sensitive decision systems and in this case the fuzzy logic can be central.

Sophisticated Fuzzy Set Extensions on the Management of Uncertainty: The frequent reference to uncertainty, fuzzy sets, intuitionistic fuzzy sets, and fuzzy clustering implies the significance of dealing with the various forms of vagueness. Theoretical extensions of fuzzy sets such as Type-2 fuzzy sets, hesitant fuzzy sets and probabilistic fuzzy models should be the focus of future research to enhance the accuracy of the modeling process through fuzzy sets to the complex decision environment.

Feature Selection and Ensemble Classification Techniques: In the light of the results of the feature selection and classification indicating high centrality measures, future studies can be carried on dynamic feature selection techniques incorporated in fuzzy classifiers. The ensemble techniques which consist of combining multiple fuzzy and crisp classifiers with adaptive feature weighting procedures may improve the accuracy of the classification, especially when the datasets are imbalanced or high-dimensional.

4.10. Determined Research Gaps using key word co-occurrences analysis

The co-occurrence analysis and network centrality metrics keyword can be viewed as an effective tool to assess the level of research saturation and unexplored gaps in the field of fuzzy logic and intelligent systems. Notwithstanding a significant amount of work, there are still a number of gaps that could be addressed in future studies:

Interpretability of Hybrid Intelligent Systems: Even though classification and diagnosis are two well-studied concepts, interpretability and explainability are still marginal. The fact that the centrality and PageRank index of such terms as interpretability and explainable artificial intelligence are quite low seems to indicate that the trade-off between model transparency and predictive power is frequently disregarded, particularly in hybrid models where fuzzy systems are paired with deep learning. This leaves a hole to be filled in future studies of interpretable fuzzy-deep architectures, especially in high-stakes systems like medical diagnostics and autonomous systems.

Fuzzy Logic IoT and Edge Environment: The newly developed domain of Internet of Things (IoT) is full of uncertainty in data, dynamicity and real-time decision-making capabilities all of which fuzzy logic are naturally very appropriate. Nevertheless, its scanty representation and lack of prominence in the network point to a gap in research in the creation of lightweight, adaptive fuzzy systems, specifically to suit resource-constrained and real-time IoT applications.

Adaptive Fuzzy Control of a Non-Linear Dynamic System: Despite the recognition of fuzzy control in the dataset, the lack of analysis of fuzzy control in the context of machine learning and optimization terms indicates that little is known about adaptive fuzzy control of non-linear, dynamic, and real world systems. This is especially applicable in real-time in areas such as robotics, smart grid management, and autonomous vehicles.

Fuzzy-Based Multimodal Data Fusion: The centrality of feature extraction is rather limited and no terms are found where multimodal or cross-domain data fusion is concerned indicating a potential that is untapped yet. Fuzzy solutions should be able to provide strong solutions to match uncertainties in cross modalities, which is becoming necessary in a variety of applications such as remote sensing, security surveillance, and biomedical monitoring.

Development and Usage of Extended Fuzzy set albeit: Despite the extensive usage of classical fuzzy sets, there exist a number of advanced models such as intuitionistic fuzzy sets, type-2 fuzzy sets, and hesitant fuzzy sets that are noted to appear infrequently and have insignificant structural roles within the network. Advanced versions provide sophisticated statefulness in the treatment of uncertainty, but are not fully exploited, in part because of their computational complexities and the unavailability of available implementation frameworks.

Applications in Socioeconomic and Environmental fields: The predominance of the literature on medical and technical applications demonstrates the absence of information on the use of fuzzy systems in more complicated socioeconomic and environmental issues. The real problem of uncertainty is also inherent in areas such as climate forecasting, planning of time-oriented policies, and behavioral economics- where fuzzy logic will be useful in offering innovative modelling and decision-support frameworks.

Combining Supervised and Unsupervised Fuzzy Models: The detachment between the fuzzy clustering and fuzzy classifier keywords, attributed to distinct clusters, reveals that there is a thin line between these two approaches. Uniting clustering and classification may improve the semi-supervised learning models, and open the doors to more powerful and versatile intelligent systems [43], [44]. Having determined the major trends and contributions based on the use of bibliometric analysis, a more specific review of the literature was conducted to determine the practical application of inference-based disease diagnosis systems based on fuzzy logic. A total of 13 chosen works which are on the sphere of human and animal health were thoroughly reviewed to comprehend how various fuzzy inference models, including Mamdani, Sugeno and Tsukamoto, have been used in the context of various diagnosis.

5. Systematic Literature Review of Selected Papers

A focused Systematic Literature Review (SLR) was performed as an additional step to the bibliometric analysis and obtain more information on the actual application of fuzzy inference techniques to medical and veterinary diagnostics [45]. A total of thirteen peer-reviewed articles published within the period between 2011 and 2024 were identified using methodological rigor, the clarity of implementing fuzzy inference, and the relevance to the disease or physiological assessment. The studies reviewed belong to a wide range of diagnostic fields, which are human disease (including kidney disease, heart disease, arthritis, malaria, and COVID-19) and veterinary health (including reproductive disorders, osteodystrophy, and poultry weight estimation). In all studies included in the paper, there is a clear description of the fuzzy inference models, membership functions, diagnostic variables and the performance outcomes [46], [47]. In the literature reviewed, the common pattern of results is that the mamdani inference model is the most prevalent, mainly because it is interpretable, and has the ability to express linguistic rules and can be used in knowledge-driven diagnostic systems. Other alternatives like sugeno and Tsukamoto are also present especially where computational efficiency or crisp numerical results are needed. Simple triangular or trapezoidal membership functions are mostly used in studies, and provide computational simplicity and professional human interpretation.

5.1. Findings:

Mamdani Dominance: Mamdani inference technique is the most widely used across both animal and human disease diagnosis systems. Its popularity stems from its interpretability and ability to handle vague and imprecise inputs through linguistic rules.

High Diagnostic Accuracy: The majority of systems exhibited a high accuracy, many exceeding 90 percent with some exceeding 98 percent accuracy with heart disease[36] as well as with chronic kidney disease[37]. This goes to validate the application of fuzzy logic in diagnostic setting where the environment is uncertain.

Flexibility to Areas of individuals: Fuzzy logic has been effectively used not only in the field of human diseases (e.g., arthritis, malaria, COVID-19, kidney and heart diseases) but also in veterinary medicine (e.g., cattle breeding diseases, bird weight prediction) as well.

Membership Functions Matter: Triangular and trapezoidal functions are the most popular as they are simple and efficient to compute. Nonetheless, more intricate functions (e.g., Gaussian) are not well studied in this dataset.

Alternative Inference and Models Emerging: Although Mamdani still stays dominant, other models such as Tsukamoto and Sugeno have demonstrated its benefits in speed and less complexity (such as Tsukamoto would not defuzzify, Sugeno would resort to linear output functions), which suggests possible efficiency improvements in real-time systems.

Hybrid Approaches seem to have potential: The application of data mining methods[39] and neutrosophic fuzzy sets [29] demonstrates a tendency to the hybrid intelligent systems that can help to improve diagnostic skills.

5.2. Identified Gaps:

Methodological Gaps

- **Excessive reliance on Mamdani models:** A very scarce effort has been made to look into adaptive or hybrid fuzzy inference systems (i.e. ANFIS, neuro-fuzzy model) that can increase learning capabilities and real-time flexibility.
- **Few Sophisticated Membership Functions:** The majority of systems utilize simple triangular or trapezoidal functions which may reduce sensitivity of the model. The advanced/adaptive membership functions are not well explored.
- **Absence of optimization methods:** Not many studies employed the use of optimization algorithms (e.g., genetic algorithms, PSO, DE) to optimize membership functions or rule bases.

- **Inadequate performance compared to deep learning models:** Fuzzy logic systems are not often compared with modern deep learning models on disease diagnosis, which would restrict the comparative knowledge.

Data and Validation Gaps

- **Large scale, real world data scarcity:** The vast majority of systems have been tested on synthetic or small scale clinical data. None of the studies mentioned cross-institutional data or outside validation on generalizability.
- **Lack of explainability measures:** All the studies did not explicitly assess interpretability or explainability, both of which are important in clinical practice.
- **No rule adaptation:** No rule bases are dynamically adapted, all systems have been found to be static in terms of their rule adaptation to new data.

Application Gaps

- **Underrepresentation of veterinary diagnostics:** In veterinary applications, fuzzy logic is more applicable than in human health, although in rural settings with resource constraints, there is under-use of fuzzy logic in animal health.
- **Poor multi-disease diagnosis:** The majority of systems only do single-disease diagnosis with no multi-condition detection systems.

5.3. Future Research Directions

To advance this domain towards publishable and deployable systems in medical and veterinary settings, the following research trajectories are proposed:

Integration with AI and Machine Learning

- Integrate deep learning or ensemble models with fuzzy systems to create hybrid diagnostic models.
- ANFIS or deep neuro-fuzzy architectures use in real-time learning and generalization.

Dynamic and Self-Optimizing Systems

- Apply biomimetic optimization strategies (e.g., GA, PSO) to automatic membership tuning and rule extraction.
- Design an online learning fuzzy system to be self updating in terms of new clinical data.

Edge and IoT Environments Expansion

- Develop lightweight fuzzy systems that can be run on a border device or wearable to facilitate mHealth (mHealth) or remote veterinary diagnosis.

Multi-Criteria and Multi-Disease Diagnosis

- Implement multi-criteria decision-making (MCDM) in fuzzy systems to manage conflicting symptoms/diagnostic pathways.
- Fazlollah, Willis and Knoop (2009) state that multi-output fuzzy models should be developed to identify comorbidities (e.g., diabetes and hypertension).

Standardization and Benchmarking

- Suggest standard fuzzy expert system datasets and evaluation protocols in healthcare in order to achieve reproducibility.
- Create public-tested and validated open-source, explainable fuzzy logic diagnostic systems.

Table 6: Review of selected studies handling uncertainty in medical and veterinary contexts

Study	**Year**	**Domain**	**Inference Technique**	**Membership Function**	**Key Application Purpose**	**Findings**	**Publication Details**
[48]	2011	Animal Disease	Mamdani	Triangular	Diagnosing 5 cattle diseases: Poly Encephalomalacia(PEM),lactation tetany(LT), Bovine Spongy Encephalopathy(BSE), Rabies, silent form(R) ,Lead poisoning , acute form(LP)	System efficiently managed uncertainty in neurological symptoms for diagnosing diseases	International Conference
[49]	2017	Animal Disease	Tsukamoto	Triangular, Trapezoidal	Diagnosing Reproductive disease(Endometritis) in Cattle	System diagnosed endomteritis in cattle with 100 % accuracy	Science Direct (Sensors Journal)
[50]	2023	Animal Disease	Sugeno	Triangular	predicting diseases of osteodystrophy, secondary acute dystrophy, ketosis, and hypomicroelementosis in cattle	According to the research, the Sugeno model yielded a result with 2% diagnostic error.	PubMed (Animals Journal)

[51]	2023	Animal Weight Estimation	Mamdani	Triangular, Trapezoidal	Estimating poultry weight	According to the findings, Mamdani inference reliably and effectively estimate the broilers weight.	PubMed (Animals Journal)
[52]	2020	Human Disease	Mamdani	Trapezoidal	Diagnosing current stage of Chronic Kidney Disease	The fuzzy expert system accurately identified 93.75% of the findings based on the confidence indicator.	Wiley (Mobile Information Systems)
[53]	2014	Human Disease	Mamdani	Triangular	Diagnosing Malaria Disease	The developed methodology improved the diagnosis of malaria in terms of accuracy and precision.	African Journal of Computing & ICT, IEEE

[54]	201	Human	Mamdani	Trapezoida	Diagnosing Arthritis	The expert	EAI Endorsed
[55]	202	Human	Mamdani	Trapezoida	Determining Coronaviru	The Expert	International Journal
[56]	202	Human	Mamdani	Triangular	Diagnosing Heart Disease	The Expert	Scopus(INTELIGENCI
[57]	202	Human	Mamdani	Triangular	Diagnosing Heart Disease	The accurac	PubMed (PLOS ONE)
[58]	201	Human	Mamdani	Trapezoida	Diagnosing Chronic Kidney	The diagnost	Journal of Theoreti
[59]	201	Human	Mamdani	Triangular	Diagnosing Malaria Disease	The Expert	International Journal
[60]	2021	Human Dis	Mamdani	Triangular, Tra	Diagnosing Coranary Artery Disease	The accuracy of Exp	PubMed (Health and technology)

6. Discussion

The landscape of fuzzy inference techniques as revealed through the bibliometric review is rich in foundational theory, as well as quickly developing towards more interdisciplinary applications. The temporal citation analysis means that the data about the interest in this sphere has not taken a linear route. But rather it has undergone a number of spurts of activity most notably during the years 2004, 2012 and more recently in 2022 and 2024. These peaks tend to be associated with the emergence of hybrid models, development of AI, or real-world difficulties that required adaptive and uncertain models. The recent surge in the rate of citation in particular is indicative of the renewed interest among scholars in the fusion of fuzzy logic with the new technologies like deep learning and artificial intelligence. Considering the authors of this study, one can notice that there is a limited number of journals, which have systematically worked on the development of the sphere. Such journals as Procedia Computer Science, Expert Systems with Applications and Applied Soft Computing are not only a place of publication but a place to meet new theories and models and applications. It stands out especially that even journals that have fewer articles, like Materials Today: Proceedings, can have a significant impact and this is evident in their remarkable citation impact. It means that the sphere is not closed to innovation on the part of unusual sources and that the quality of contributions is highly appreciated irrespective of the quantity.

This is further elaborated in the author level analysis. Well-known figures such as Francisco Herrera, Joao M.C. Sousa and Susana M. Vieira have significantly contributed to the development of the field, not just in terms of the quantity of publications but also in terms of scholarly influence based on h-index, g-index and m-index indicators. In the intervening period, a fresh generation of writers - publishing about 2022 - have already been highly visible, they tend to be collaborative and high-impact. An examination of the key-word distribution provides a thematic map of the existing issues in the field and its future. Such terms as Fuzzy Sets and Fuzzy Logic are prevalent in numbers, which proves the importance of these terms as the conceptual keystones of the research field. Nevertheless, the most striking thing is the simultaneous increase in such terms as Machine Learning, Deep Learning, and Artificial Intelligence. The keywords Diagnosis, Classification, and Expert Systems indicate that fuzzy inference has been having a rich field to play in application-oriented fields especially in areas where the decision maker is under uncertainty like in healthcare, fault detection, and automated reasoning. In a similar way, the focus on Feature Selection, Interpretability, and Transparency is an indication of how the field is responding to modern-day needs of responsible and comprehensible AI, particularly in high-stakes settings. A key observation made during the research is that the Sugeno model has been adopted preferentially in situations when computational efficiency and precision are needed. Here, every rule results in a crisp number which is computed using a mathematical function and simplifies the process of aggregation to a weighted average. This comes as a relief of the computational cost of the classic defuzzification operations- a task that may be time-consuming and mathematically intensive in such models as Mamdani. This simplified process makes the Sugeno model a desirable option in the engineering field and data-driven situations, particularly when a linear relation between input and output parameters is known or needed.

The Tsukamoto model is similar to Sugeno in that it produces crisp outputs but the model has constraints on the rigidity of its membership functions requiring them to be monotonically increasing or decreasing. Although it has the advantage of not defuzzifying, it has a smaller application range and is more context specific. The logic processing in the model does not follow the normal composition operations in the configuration of Mamdani systems, but this exception makes the model to keep clarity in the output even when the linguistic variables in the model are stated using fuzzy expressions. The Mamdani model, on the contrary, does not lose its topicality as it can be applied to those situation when the human interpretability and the linguistic representation of decision rules take precedence over the computational economy. Its use in practical applications has mainly been promoted by its intuitiveness or easy appeal- each rule is used to relate the inputs to the fuzzy outputs which are defuzzified to come up with conclusions. Mamdani can also be a trusted option in systems that demand qualitative analysis, and thus where finesse and human-like decisions are preferred; it is also more capable of supporting complex rule-based structures than other options because it has a higher computational cost, although its upper computational cost is less than that of some other options.

7. Conclusion

The work provides an in-depth summary of the research tendency and thematic trends in the world and the fuzzy inference techniques. It exposes the fact that the field has evolved over time since a purely theoretical framework, into a wide, application-focused field, but now more influenced by the evolution of artificial intelligence and data science. The analysis supports the claim that as much as Mamdani model will continue to be a positive option in human-interpretable systems given its ability to handle linguistic expressions and its simplicity, it can be computationally expensive given that it has defuzzification step. However, the Sugeno model, due to having the capability of producing crisp results by the weighted linear functions, provides more accuracy and performance particularly when dealing with systems that need to be performed in real-time. It is especially useful when quantitative relationships are more well defined such as in the field of disease diagnosis. The Tsukamoto model, which is not so common, does not require defuzzification and provides sharp results under certain circumstances, so it can be applied to the narrowly structured applications.

Keywords co-occurrence analysis also shows a trend to shift to hybrid, explainable AI systems, and pay more attention to interpretability, machine learning integration, and optimization. The insights provided by the cluster toward the different applications include the expert systems and diagnostics to the optimization by the use of genetic algorithms. The existence of some few powerful journals and authors highlights the intellectual centers of the field that are a consistent source of innovation. To sum up, it is clear and moving forward that fuzzy inference systems are not only surviving but developing. Their uncertainty processing capabilities, domain-specific adaptable capabilities, and their capacity to process linguistic and quantitative reasoning make them invaluable in the contemporary data-driven world. Since AI issues require accuracy and interpretability, fuzzy models are placed in an excellent position to achieve these requirements and keep influencing intelligent, human-friendly solutions.

References

[1] J. A. Goguen, "L. A. Zadeh. Fuzzy sets. Information and control, vol. 8 (1965), pp. 338–353. - L. A. Zadeh. Similarity relations and fuzzy orderings. Information sciences, vol. 3 (1971), pp. 177–200.," *Journal of Symbolic Logic*, vol. 38, no. 4, pp. 656–657, 1973, doi: DOI: 10.2307/2272014.

[2] L. A. Zadeh, "Is there a need for fuzzy logic?," *Inf Sci (N Y)*, vol. 178, no. 13, pp. 2751–2779, 2008, doi: https://doi.org/10.1016/j.ins.2008.02.012.

[3] H. Carter, "Fuzzy Sets and Systems — Theory and Applications," *Journal of the Operational Research Society*, vol. 33, no. 2, p. 198, 1982, doi: 10.1057/jors.1982.38.

[4] V. Radu, F. Radu, A. I. Tabirca, S. I. Saplacan, and R. Lile, "Bibliometric Analysis of Fuzzy Logic Research in International Scientific Databases," *International journal of computers, communications & control*, vol. 16, no. 1, 2021, doi: 10.15837/ijccc.2021.1.4120.

[5] X. DJAM, G. Wajiga, H. Yisa, and N. Blamah, "A Fuzzy Expert System for the Management of Malaria," *Int J Pure Appl Sci Technol*, vol. 5, pp. 84–108, Jan. 2011.

[6] S.-M. Chen and C.-A. Tsai, "Multiattribute decision making using novel score function of interval-

valued intuitionistic fuzzy values and the means and the variances of score matrices," *Inf Sci (N Y)*, vol. 577, pp. 748–768, 2021, doi: https://doi.org/10.1016/j.ins.2021.07.055.

[7] O. Castillo and P. Melin, "A review on interval type-2 fuzzy logic applications in intelligent control," *Inf. Sci.*, vol. 279, pp. 615–631, 2014, [Online]. Available: https://api.semanticscholar.org/CorpusID:20792524

[8] K. Coussement, M. Z. Abedin, M. Kraus, S. Maldonado, and K. Topuz, "Explainable AI for enhanced decision-making," *Decis Support Syst*, vol. 184, p. 114276, 2024, doi: https://doi.org/10.1016/j.dss.2024.114276.

[9] P. Dutta and A. Konwar, "Quintic fuzzy sets: A new class of fuzzy sets for solving multi-criteria decision-making problems under uncertainty," *Decision Analytics Journal*, vol. 11, p. 100449, 2024, doi: https://doi.org/10.1016/j.dajour.2024.100449.

[10] J. Cao *et al.*, "Fuzzy inference system with interpretable fuzzy rules: Advancing explainable artificial intelligence for disease diagnosis—A comprehensive review," *Inf Sci (N Y)*, vol. 662, p. 120212, 2024.

[11] T. Madhumathi and F. N. Irudayam, *Recent Trends in Fuzzy Set Theory and its Applications IIP Series NEUTROSOPHIC CHAOTIC B-CLOSED SET IN NEUTROSOPHIC CHAOTIC TOPOLOGICAL SPACE NEUTROSOPHIC CHAOTIC B-CLOSED SET IN NEUTROSOPHIC CHAOTIC TOPOLOGICAL SPACE IIP Series NEUTROSOPHIC CHAOTIC B-CLOSED SET IN NEUTROSOPHIC CHAOTIC TOPOLOGICAL SPACE*.

[12] V. Cherkassky, "Fuzzy Inference Systems: A Critical Review," in *Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications*, O. Kaynak, L. A. Zadeh, B. Türkşen, and I. J. Rudas, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 1998, pp. 177–197.

[13] T. M. Alam *et al.*, "Disease diagnosis system using IoT empowered with fuzzy inference system," *Comput. Mater. Contin*, vol. 70, pp. 5305–5319, 2022.

[14] A. Di Vaio, R. Palladino, R. Hassan, and O. Escobar, "Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review," *J Bus Res*, vol. 121, pp. 283–314, 2020, doi: https://doi.org/10.1016/j.jbusres.2020.08.019.

[15] P. Danese, V. Manfè, and P. Romano, "A Systematic Literature Review on Recent Lean Research: State-of-the-art and Future Directions," *International Journal of Management Reviews*, vol. 20, no. 2, pp. 579–605, Apr. 2018, doi: https://doi.org/10.1111/ijmr.12156.

[16] M. Christofi, E. Leonidou, and D. Vrontis, "Marketing research on mergers and acquisitions: a systematic review and future directions," *International Marketing Review*, vol. 34, no. 5, pp. 629–651, Sep. 2017, doi: 10.1108/IMR-03-2015-0100.

[17] M. Akin, S. P. Eyduran, and V. Krauter, "Food packaging related research trends in the academic discipline of food science and technology: A bibliometric analysis," *Cleaner and Circular Bioeconomy*, vol. 5, p. 100046, 2023, doi: https://doi.org/10.1016/j.clcb.2023.100046.

[18] M. Aria and C. Cuccurullo, "bibliometrix: An R-tool for comprehensive science mapping analysis," *J Informetr*, vol. 11, no. 4, pp. 959–975, 2017, doi: https://doi.org/10.1016/j.joi.2017.08.007.

[19] "R: A Language and Environment for Statistical Computing." [Online]. Available: https://www.gnu.org/copyleft/gpl.html.

[20] D. Bottomly *et al.*, "Integrative analysis of drug response and clinical outcome in acute myeloid leukemia," *Cancer Cell*, vol. 40, no. 8, pp. 850–864, 2022.

[21] S. Ali *et al.*, "Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence," *Information Fusion*, vol. 99, p. 101805, 2023, doi: https://doi.org/10.1016/j.inffus.2023.101805.

[22] W. Zhou, X. Liu, H. Bai, and L. He, "Intelligent medical diagnosis and treatment for diabetes with deep convolutional fuzzy neural networks," *Inf Sci (N Y)*, vol. 677, p. 120802, 2024, doi: https://doi.org/10.1016/j.ins.2024.120802.

[23] M. A. Khan and F. Algarni, "A Healthcare Monitoring System for the Diagnosis of Heart Disease in the IoMT Cloud Environment Using MSSO-ANFIS," *IEEE Access*, vol. 8, pp. 122259–122269, 2020, doi: 10.1109/ACCESS.2020.3006424.

[24] N. Gupta, H. Singh, and J. Singla, "Fuzzy Logic-based Systems for Medical Diagnosis – A Review," in *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2022, pp. 1058–1062. doi: 10.1109/ICESC54411.2022.9885338.

[25] T. M. Alam *et al.*, "A fuzzy inference-based decision support system for disease diagnosis," *Comput J*, vol. 66, no. 9, pp. 2169–2180, 2023.

[26] M. A. A. Najm, K. S. Abd-Alrassol, Q. A. Qasim, H. H. Hussein, and H. N. K. AL-Salman, "Materials Today: Proceedings," 2021.

[27] P. Nagaraj and P. Deepalakshmi, "An intelligent fuzzy inference rule-based expert recommendation system for predictive diabetes diagnosis," *Int J Imaging Syst Technol*, vol. 32, no. 4, pp. 1373–1396, 2022.

[28] L. Zhang, Y. Yao, and P. Zhu, "Shadowed set approximations of L-fuzzy sets," *Inf. Sci.*, vol. 679, no. C, Sep. 2024, doi: 10.1016/j.ins.2024.121094.

[29] H. D. Arora and A. Naithani, "A new definition for quartic fuzzy sets with hesitation grade applied to multi-criteria decision-making problems under uncertainty," *Decision Analytics Journal*, vol. 7, p. 100239, 2023, doi: https://doi.org/10.1016/j.dajour.2023.100239.

[30] N. V. E. S. Murthy and J. Prasanna, "A Theory of Lattice-Valued Fuzzy Sets and Fuzzy Maps Between Different Lattice-Valued Fuzzy Sets – Revisited," *International Journal of Advanced Research in Computer Science*, vol. 4, pp. P262-286, Jan. 2013.

[31] H. Liao and Z. Xu, "Hesitant Fuzzy Set and Its Extensions," in *Hesitant Fuzzy Decision Making Methodologies and Applications*, H. Liao and Z. Xu, Eds., Singapore: Springer Singapore, 2017, pp. 1–36. doi: 10.1007/978-981-10-3265-3_1.

[32] T. Senapati and R. R. Yager, "Fermatean fuzzy sets," *J Ambient Intell Humaniz Comput*, vol. 11, no. 2, pp. 663–674, 2020, doi: 10.1007/s12652-019-01377-0.

[33] S. Ashraf, "Disc Spherical Fuzzy Sets and Their Application in Decision Making," in *Intelligent and Fuzzy Systems*, C. Kahraman, S. Cevik Onar, S. Cebi, B. Oztaysi, A. C. Tolga, and I. Ucal Sari, Eds., Cham: Springer Nature Switzerland, 2024, pp. 666–674.

[34] A. Al-Husban, "Bipolar Complex Intuitionistic Fuzzy Sets," *Earthline Journal of Mathematical Sciences*, vol. 8, no. 2, Jan. 2022, doi: 10.34198/ejms.8222.273280.

[35] X. Peng and G. Selvachandran, "Pythagorean fuzzy set: state of the art and future directions," *Artif Intell Rev*, vol. 52, no. 3, pp. 1873–1927, 2019, doi: 10.1007/s10462-017-9596-9.

[36] T. Runkler, S. Coupland, and R. John, "Interval type-2 fuzzy decision making," *International Journal of Approximate Reasoning*, vol. 80, pp. 217–224, 2017, doi: https://doi.org/10.1016/j.ijar.2016.09.007.

[37] B. C. Cuong and V. Kreinovich, "Picture fuzzy sets - A new concept for computational intelligence problems," in *2013 Third World Congress on Information and Communication Technologies (WICT 2013)*, 2013, pp. 1–6. doi: 10.1109/WICT.2013.7113099.

[38] K. Mittal, A. Jain, K. S. Vaisla, O. Castillo, and J. Kacprzyk, "A comprehensive review on type 2 fuzzy logic applications: Past, present and future," *Eng Appl Artif Intell*, vol. 95, p. 103916, 2020, doi: https://doi.org/10.1016/j.engappai.2020.103916.

[39] K. T. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets Syst*, vol. 20, no. 1, pp. 87–96, 1986, doi: https://doi.org/10.1016/S0165-0114(86)80034-3.

[40] S. T. Homer and W. M. Lim, "Theory development in a globalized world: Bridging 'doing as the romans do' with 'understanding why the romans do it,'" *Global Business and Organizational Excellence*, vol. 43, no. 3, pp. 127–138, 2024.

[41] J. J. Salovaara, J. Pietikäinen, and H. Cantell, "Perceptions of interconnected sustainability: Students' narratives bridging transition and education," *J Clean Prod*, vol. 281, p. 125336, 2021.

[42] X. Ma, Y. Wang, Y. Wang, X. Cai, and Y. Han, "Survey on chiplets: interface, interconnect and integration methodology," *CCF Transactions on High Performance Computing*, vol. 4, no. 1, pp. 43–52, 2022.

[43] J. S. R. Jang, C. T. Sun, and E. Mizutani, "Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence [Book Review]," *IEEE Trans Automat Contr*, vol. 42, no. 10, pp. 1482–1484, 1997, doi: 10.1109/TAC.1997.633847.

[44] A. Adeli and M. Neshat, "A Fuzzy Expert System for Heart Disease Diagnosis," *Lecture Notes in Engineering and Computer Science*, vol. 2180, Mar. 2010.

[45] I. Passas, "Bibliometric analysis: the main steps," *Encyclopedia*, vol. 4, no. 2, 2024.

[46] W. Wang *et al.*, "An interpretable intuitionistic fuzzy inference model for stock prediction," *Expert Syst Appl*, vol. 213, p. 118908, 2023.

[47] S.-C. Vanegas-Ayala, J. Barón-Velandia, and D.-D. Leal-Lara, "A systematic review of greenhouse humidity prediction and control models using fuzzy inference systems," *Advances in Human-Computer Interaction*, vol. 2022, no. 1, p. 8483003, 2022.

[48] M. Jampour, M. Jampour, M. Ashourzadeh, and M. Yaghoobi, "A Fuzzy Expert System to Diagnose Diseases with Neurological Signs in Domestic Animal," in *2011 Eighth International Conference on Information Technology: New Generations*, 2011, pp. 1021–1024. doi: 10.1109/ITNG.2011.217.

[49] Suharjito, Diana, Yulyanto, and A. Nugroho, "Mobile Expert System Using Fuzzy Tsukamoto for Diagnosing Cattle Disease," *Procedia Comput Sci*, vol. 116, pp. 27–36, 2017, doi: https://doi.org/10.1016/j.procs.2017.10.005.

[50] D. Turimov Mustapoevich, D. Muhamediyeva Tulkunovna, L. Safarova Ulmasovna, H. Primova, and W. Kim, "Improved Cattle Disease Diagnosis Based on Fuzzy Logic Algorithms," *Sensors*, vol. 23, no. 4, Feb. 2023, doi: 10.3390/s23042107.

[51] E. Küçüktopçu, B. Cemek, and H. Simsek, "Application of Mamdani Fuzzy Inference System in Poultry Weight Estimation," *Animals*, vol. 13, pp. 1–16, Jul. 2023, doi: 10.3390/ani13152471.

[52] J. Singla *et al.*, "A Novel Fuzzy Logic-Based Medical Expert System for Diagnosis of Chronic Kidney Disease," *Mobile Information Systems*, vol. 2020, pp. 1–13, Jun. 2020, doi: 10.1155/2020/8887627.

[53] P. Dagar, A. Jatain, and D. Gaur, *Medical diagnosis system using fuzzy logic toolbox*. 2015. doi: 10.1109/CCAA.2015.7148370.

[54] S. Siddiqui *et al.*, "Diagnosis of Arthritis Using Adaptive Hierarchical Mamdani Fuzzy Type-1 Expert System," *EAI Endorsed Transactions on Scalable Information Systems*, Nov. 2019, doi: 10.4108/eai.13-7-2018.161439.

[55] P. Ejodamen and V. Ekong, "A Fuzzy Expert System Model for the Determination of Coronavirus Disease Risk," vol. 11, pp. 4825–4831, Jan. 2021.

[56] T. Kasbe, "FRBF: A Fuzzy Rule Based Framework for Heart Disease Diagnosis," *Inteligencia Artificial*, vol. 25, pp. 122–138, May 2022, doi: 10.4114/intartif.vol25iss69pp122-138.

[57] Md. L. Ali, M. S. Sadi, and Md. O. Goni, "Diagnosis of heart diseases: A fuzzy-logic-based approach," *PLoS One*, vol. 19, no. 2, pp. e0293112-, Feb. 2024, [Online]. Available: https://doi.org/10.1371/journal.pone.0293112

[58] M. Muslim, I. Kurniawati, and E. Sugiharti, "Expert system diagnosis chronic kidney disease based on mamdani fuzzy inference system," vol. 78, pp. 70–75, Aug. 2015.

[59] X. DJAM, G. Wajiga, H. Yisa, and N. Blamah, "A Fuzzy Expert System for the Management of Malaria," *Int J Pure Appl Sci Technol*, vol. 5, pp. 84–108, Jan. 2011.

[60] L. J. Muhammad and E. A. Algehyne, "Fuzzy based expert system for diagnosis of coronary artery disease in nigeria," *Health Technol (Berl)*, vol. 11, no. 2, pp. 319–329, 2021, doi: 10.1007/s12553-021-00531-z.