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Fuzzy Sets-Based Approaches for Improved Medical Diagnosis: An Analysis and Overview of Major Research Directions

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Today's sedentary lifestyle gives rise to a variety of diseases, making its accurate diagnosis quite essential so that proper treatment can be provided. Computational and artificial intelligence (AI) based approaches can be used to diagnose with better accuracy and reliability, and the process can be automated. However, medical diagnosis encompasses complex decision-making procedures that are often associated with uncertainty and imprecise information. Though fuzzy sets and systems have been effectively used for medical diagnosis, further attention is required to arrive at intelligent and expert systems for better and more accurate diagnosis. In this paper, we present a comprehensive overview of the fuzzy sets-based approaches utilized for diagnosis in the medical domain, and conduct a bibliometric analysis of the publications in fuzzy medical diagnosis.

CCS CONCEPTS • Computing methodologies → Artificial intelligence, Applied Computing → Life and medical sciences

Additional Keywords and Phrases: Fuzzy sets, medical diagnosis, keywords analysis, theme identification, overview

1 INTRODUCTION

The emphasis on public health is necessarily influenced by the evolving characteristics of the population. With the current dynamic circumstances, especially post pandemic, efficient medical diagnosis has taken precedence for both the scientific community and governmental institutions. Generally, medical diagnosis involves a variety of steps like, symptom analysis, clinical tests, integration of complex medical data, and medical data analytics. Together, the objective of these processes is to generate clear and actionable conclusions across a wide variety of diseases and health conditions. In many cases, diseases grow gradually after the initial symptoms manifest themselves, which may be present in varying degrees of severity, thus complicating the diagnostic process and making it of a longer duration. For instance, certain conditions may develop silently over time, which only become apparent when they have developed to a critical stage. A disease like Diabetes Mellitus (DM), for example, which occurs when blood glucose levels become abnormally high in the human body. DM can occur at any stage, but its predominance rises steeply with age [203]. The importance of early detection and precise diagnosis in DM that can identify subtle deviations from normal health parameters before more severe complications arise cannot be overemphasized. A sudden rise in cases in the recent health crisis has further underlined the vulnerability of individuals with underlying conditions, and thus the need for robust and rapid diagnostic tools that can adapt to emerging challenges in public health. With efficient non-clinical methods, early precautions could be initiated which would help people in maintaining their health, enabling them to lead long and healthy lives. It is thus crucial to aim for accurate results in treatment, safety of patients, competent health management, etc., which can be achieved by integrating computational approaches into health care, to ensure an optimal healthcare system with the focus on the well-being of the people.

Using computational and artificial intelligence (AI)-based approaches, including novel machine learning (ML) techniques, we can utilize the potential of the data for better accuracy, reliability, and automation of the diagnostic processes. The ML and AI models learns constantly from new data to provide refined outcomes by also integrating updated medical research. Several specific applications with successful use cases are pattern recognition, risk prediction and forecasting, image analysis, and precision in the prescription of the dosage, etc. However, due to the complex nature of medical, the analysis is hugely affected by uncertainty due to the presence of the inherent noise. The data varies from medical documentation, reading from the clinical tests, etc., and the noise could be in the form of reading from devices, error margins, missing values, etc., [204], [205]. Furthermore, the involvement of multiple experts or medical professionals' opinions create vagueness in the decision-making process. Such type of uncertainties can be handled with the help of the probability theory. However, a greater degree of freedom is provided by the fuzzy set theory (FST) or fuzzy logic (first proposed by Prof. Zadeh in 1965), which is complementary to the probability theory rather than competitive [206]. Fuzzy sets (FSs) are totally different from classical sets as they have the freedom to argue beyond the boundaries of a set. In many real-world situations, using only binary membership for an element is not justified. FSs, traditionally also called type-1 fuzzy sets (T1 FSs), can easily model the uncertainty and imprecision in the data sets, which was the main drawback of classical sets. FSs form the bridge between the uncertain and certain environments of medical diagnosis. This makes fuzzy approaches suitable for dealing with complex medical and patient data. As a result, they can improve diagnostic accuracy, support early intervention strategies, and eventually lead to more personalized treatment plans. Therefore, it is essential to study the novel FSs-based approaches in the application of medical diagnosis.

Traditional FSs have now evolved into a variety of advanced variants, including intuitionistic FSs, type-2 fuzzy sets (T2 FSs), etc. [224]. These developments have enhanced the mathematical modelling of uncertainty along with effectively managing linguistic ambiguities which makes them particularly valuable in the domain of medical diagnosis. Therefore, in this work, we extensively study the role of various variants of fuzzy uncertainty modelling approaches in medical diagnosis. These approaches are: FSs, T2 FSs, Computing with Words (CWW), perceptual computing (Per-C), inference engines, etc. Each of them is explained in detail in the next section. To glean insights about the spectrum of this research domain, we have also conducted a bibliometric analysis of the publications. This paper also includes an extensive literature overview that covers a wide variety of medical issues addressed by these and related methods, which revealed a taxonomy of medical diagnosis problems solved with several fuzzy techniques, highlighting how they have contributed to an improved diagnostic process.

The rest of the paper is organized as follows. Section 2 provides the standard definitions and FSs-based approaches used in medical diagnosis. A brief and related bibliometric analysis is performed in Section 3. Section 4 discusses extensively the overview of the literature in the area of FSs-based approaches for medical diagnosis. Finally, Section 5 discusses the outcomes and provides a conclusion.

2 PRELIMINARIES ON FUZZY SETS-BASED APPROACHES

This section presents the mathematical preliminaries and overview of the standard fuzzy sets-based approaches

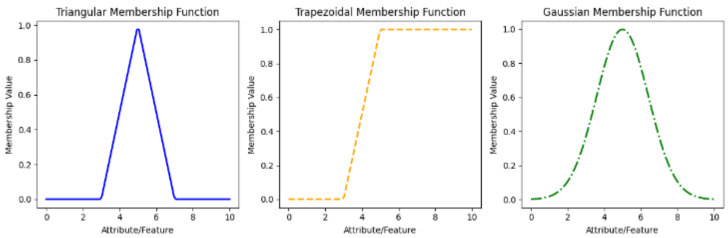

Fig.1. Typical fuzzy membership function shapes.

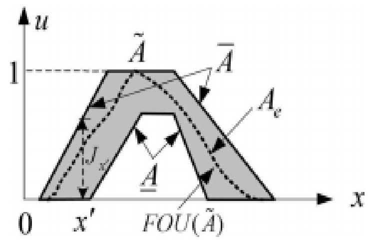

Fig. 2: FOU, UMF and LMF

used in handling the issues related to the problem of medical diagnosis.

2.1 Fuzzy Sets

A fuzzy set (also termed as type-1 fuzzy set (T1 FS)), A, is represented by an ordered pair $\{x, \mu_A(x): x \in X\}$, where $\mu_A(x): X \to [0,1]$ is the membership value of A, and X is the universe of discourse. The FSs are characterized by membership function (MF) which may be of different shapes and types. Most commonly used MF's are: Triangular MF, Trapezoidal MF, Gaussian MF, etc. which are depicted in Fig. 1. The Attribute/feature could be specific to application in medical diagnosis which is generally an uncertain variable for which the MF has been constructed.

2.2 Type-2 fuzzy sets

Type-2 Fuzzy Sets (T2 FSs) have two grades of membership, i.e. primary membership value and secondary membership value [161]. They are defined as memberships of membership value and can be represented as:

$$\tilde{A} = \left\{\left((x,u), \mu_{\tilde{A}}(x,u)\right) |\ x \in X, u \in [0,1]\right\} \tag{1}$$

where, x is a primary variable as above and u is membership value for each $x \in X$ and $0 \le \mu_{\tilde{A}}(x,u) \le 1$. However, due to the computational aspect with T2 FSs, Interval Type-2 Fuzzy Sets (IT2 FSs) are often used in various applications [162]. An IT2 FS, $\tilde{A}_I$ is given by the MF $\mu_{\tilde{A}_I}(x,u)$, where $x \in X$ and $\mu_{\tilde{A}} \in J_x[0,1]$, i. e.,

$$\tilde{A}_I = \left\{\left((x,u), \mu_{\tilde{A}}(x,u) = 1\right) \middle| \forall x \in X, \forall u \in\ j_x \subseteq [0,1]\right\} \tag{2}$$

where x is a primary variable with domain X; $\mu \in [0,1]$ which is the secondary variable, has domain $J_x \subseteq [0,1]$at each $x \in\ X$; J_x is primary membership of x and $\mu_{\tilde{A}}$ is the secondary grade of x which equals to 1 $\forall x \in X$and $\forall u \in J_x \subseteq [0,1]$ [226]. For the IT2 FSs, the uncertainty about a fuzzy set is conveyed by the union of all its primary membership values and is called the footprint of uncertainty (FOU) (see Fig 2). The upper membership value (UMF) and the lower membership value (LMF) are T1 FSs that form the FOU. It is represented as follows:

$$\text{FOU}\ (\tilde{A}) = \ \cup_{x \in X} J_x, \text{ where } J_x = [\mu_{\underline{A}}(x), \mu_{\overline{A}}(x)] \tag{3}$$

2.3 Fuzzy Linguistic Approaches

Humans communicate in words which are often vague and, ambiguous and thus uncertain. Fuzzy logic (FL) and fuzzy sets form the basis of semantic approaches where uncertain or vague attributes in communication are assigned semantic values where each term has a meaning and a label with it. The label is the sentence and the meaning is the fuzzy subset. The models formed using this approach follow approximate reasoning. There are various fuzzy linguistic approaches like linguistic summarization, Perceptual Computing (Per-C), Computing with Words (CWW) etc. [2] - [4], which are briefly described as follows:

2.3.1 Computing with Words (CWW) Technique

The Computing with Words (CWW) is a technique in which words are used to represent reasoning and computing, rather than numbers [2].

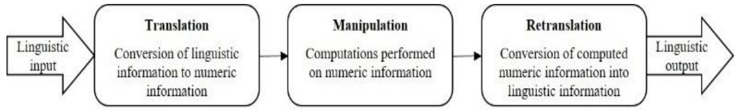

Fig. 3: Yager's scheme of CWW

Patients generally depict clinical indications through words which are unclear and may be interpreted differently by different individuals. To capture such word uncertainties, the CWW paradigm was proposed [1], where computation involves words drawn from natural languages. A simple block-based scheme of CWW, introduced by Yager [201] can be viewed in Fig. 3.

2.3.2 Perceptual Computing

Utilizing the CWW engine, Mendel proposed a specific type of architecture, i.e., Per-C, which is used to interpret subjective decisions [202]. Per-C has been utilized in various applications and domains such as investment decision-making [164], social judgment making [165], distributed decision making [162], and hierarchical and distributed decision-making [166]. In summary, Per-C is the first full implementation of Zadeh's CWW paradigm, applied to assisting people in making subjective judgements. Per-C follows an architecture as mentioned in Fig. 4 which has 3 components: an encoder which takes words as inputs and forms fuzzy sets; a CWW engine and a decoder that generates output. With the aim of appropriately modelling qualitative factors provided as linguistic responses, a Per-C-based linguistic decision support system may be used for non-clinical diagnosis of medical issues of individuals. Especially, in cases of DM, this process of prediction of diabetes using Per-C is termed as POD Per-C. The POD Per-C model has been developed with inputs from a group of experts, who duly provided their expertise in identifying the most appropriate parameters of the model. They also provided the numerical ranges for these parameters along with the diagnosis for the test cases considered.

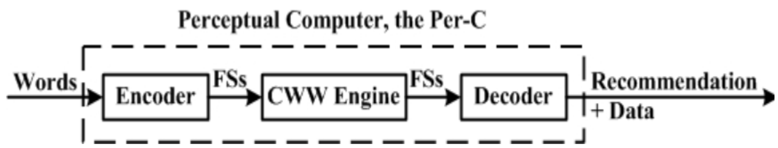

Fig. 4: Architecture of Perceptual Computing (Per-C)

2.3.3 Linguistic Summarization

Fuzzy linguistic summarization provides summaries that basically help in understanding datasets well in advance [4]. It provides truth value with each summary that depicts the validity of the summary. A summary of a dataset consists of three parts, viz. (1) a summarizer (S), (2) a quantity in agreement (Q) and, (3) a measure of validity (T). For instance, consider that a dataset, $P = \{3,5,7,8,11,15\}$ is the set of marks obtained by students. We can discuss summaries in the form: $S =$ "$about\ 10$", $Q =$"$Most$" + "...$therefore\ most\ \ of\ the\ marks\ are\ \ about\ 10$". For different summarizers we obtain different values of T. The data has to be summarized with the help of the summarizer (S). The summarizers can hold linguistic or numeric values. The linguistic values given to the summarizers depend on how those linguistic values are accommodated in the FSs. As an example, consider a set $F = \{1,3,4,6\}$, where we can represent its summarizer as "near 6" and then accommodate it in an FS as $\{0/1, 0.5/3, 0.6/4, 1/6\}$. The next part of LS is quantity in agreement (Q). This indicates the quantity to which the summarizer satisfies the data. The next part in LS is degree of truth that basically depicts the validity of the summary. If, $S(d_i)$ is the proportion of the dataset D which satisfies S, then T is calculated as follows:

$$T = Q(r), where\ r = \frac{1}{n} * \sum_{i=1}^{n} S(d_i) \quad (4)$$

2.3.4 Perceptual Computing and Linguistic Summarization in Healthcare

In many countries, the cost of technological consultation is often cheaper than visiting a healthcare professional. The domain of fuzzy logic, linguistic summarization and Per-C have also played an important role in the realm of medical diagnosis and related areas [5]-[9]. For example, a fuzzy inference system was developed in [10] to support medical diagnosis in real time through customer risk mapping. Per-C is used in diagnosis of heart diseases [11] and was called as heart monitoring through perceptual computing (HMT-Per-C). Fuzzy classification of pixels was utilized in [12] to segment skin lesions in ceroscopy images. Also, fuzzy rules were put to use in [13], along with other methods to improve the classification performance of neural networks, which was tested on key chronic diseases. Application of fuzzy logic and intuitionistic fuzzy logic has been studied in the domain of medical diagnosis in [14]. Recently, a close-loop drug administration mechanism was developed based on an interval type-2 fuzzy logic control in [15], to control mean arterial blood pressure. Additionally, a survey [16] was performed to study the existing fuzzy decision support systems for diagnosing musculoskeletal disorders. Specifically, diabetes is a long-haul ailment and International Diabetes Federation report suggests that almost 11% of adult population around the globe is troubled by it [17]. Several fuzzy based approaches have been utilized to diagnose DM within individuals.

2.4 Fuzzy Inference System

Another fuzzy sets-based approach, which is often used for medical diagnosis problems is called fuzzy inference systems (FISs). There are four main components in this system where the first component is Fuzzy inference that takes input and converts them to the fuzzy sets. This step is called fuzzification. The second component is a knowledge-based component that holds expert recommendations and is used to get to an inference which is the third component. The fourth component is defuzzification, that produces a crisp output for final decision making [20]. A typical fuzzy inference system is depicted in Fig. 5

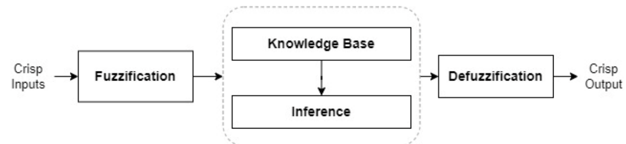

Fig. 5. Fuzzy Inference System

3 ANALYSIS OF PUBLICATIONS IN FUZZY MEDICAL DIAGNOSIS

We performed an analysis of the publications related to the domain of FSs and medical diagnosis. The purpose of this section to understand how academia has evolved in this area over the years. It also explores the key areas of research with the help of keywords analysis. The steps taken are mentioned in Fig. 6. First, we select the data repository for the collection of bibliometric data, which is the Web of Science data base because of the quality of its indexed papers. In the data extraction step, we identified the relevant keywords for the query to execute. The first part of the query contains all the possible combinations of fuzzy set techniques such as type-1 fuzzy, type-2 fuzzy, fuzzy sets, fuzzy logic, Per-C, fuzzy inference, computing with word, Fuzzy Linguistic, fuzzy rule-based, and fuzzy rule base. The result from the first part is intersected with the keywords 'medical' and 'diagnosis'. Till the time of writing, the query returned 1003 entries where the first paper was listed in 1986. Fig. 7 shows the number of publications and citations over the years, respectively, till 2024. Table 1 lists the publication types in the field, where we see that article counts to ∼96% of all the publications.

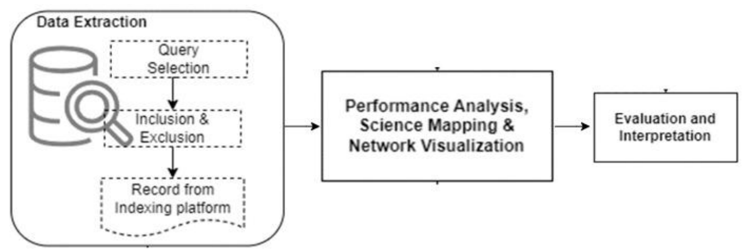

Fig. 6. Flowchart for the publication analysis

Table 1: Publication types

Document Types	Record Count	% of 1003
Article	962	95.91
Review Article	40	3.99
Proceeding Paper	30	2.99
Early Access	20	1.99
Retracted Articles	7	0.70
Data Paper	1	0.10
Letter	1	0.10

Citation topics analysis

As can be seen from Fig. 7, the first few publications in the area of Fuzzy sets-based medical diagnosis were indexed 30 years ago. Over the years, early areas of research and certain topics with strong prominence may have diminished. The citation topics by WOS is one solution which can ease the process of individually investigating the

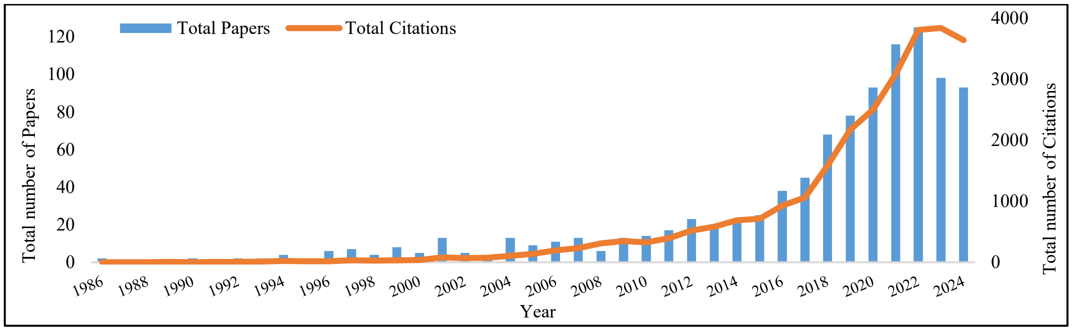

Fig. 7. Total number of publications and citations over the years

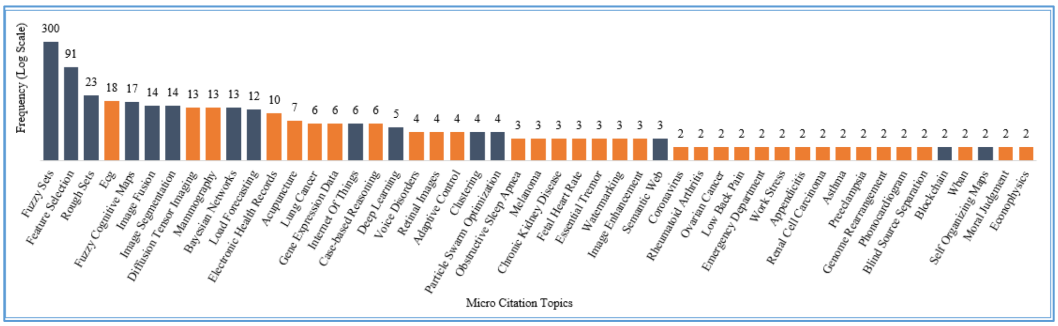

Fig. 8: Micro citation topics in Fuzzy Medical diagnosis

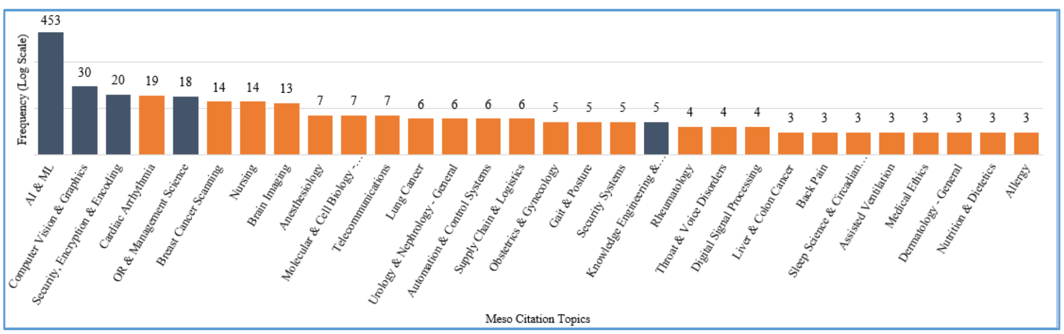

Fig. 9: Meso citation topics in Fuzzy Medical diagnosis

huge number of papers. This is the approach that provides insights into the papers which are interconnected through their citations, which makes a strong case for their relatedness. This means that papers with strong citation connections will have a similar scope and thus can be clubbed into one cluster. Such clusters are further classified into various levels such as macro, meso, and micro, providing different levels of detail. In our study, we have provided the micro and meso classifications, which are depicted in Figs. 8 & 9. The micro classification is dominated by papers in fuzzy sets, feature selections, rough sets, fuzzy cognitive maps, etc. while the meso classification is dominated by the papers in AI & ML, computer vision and graphics, security, encryption and encoding, etc. One limitation of this approach is the inclusion of papers only 1980 onwards. However, for our study this is not an issue.

Figs. 10 & 11 represent the co-occurrence analysis and the cluster view from the all the keywords and authors keywords, respectively. The bigger node in the figure represents the keyword which has more weight and which has appeared a greater number of times. The link between any two nodes represents the fact that the keywords appear together in the papers. So, for instance, similarity measures and pattern recognition appeared more often in papers. The thickness of the link between the keywords indicates the co-occurrence strength of these keywords, implying that they appeared together more often. Overall, from the figures it can be concluded that "medical diagnosis" is the central node indicating its strong co-occurrence strength with other keywords such as "fuzzy logic", "uncertainty", "fuzzy sets", "decision making", "intuitionistic fuzzy sets", etc.

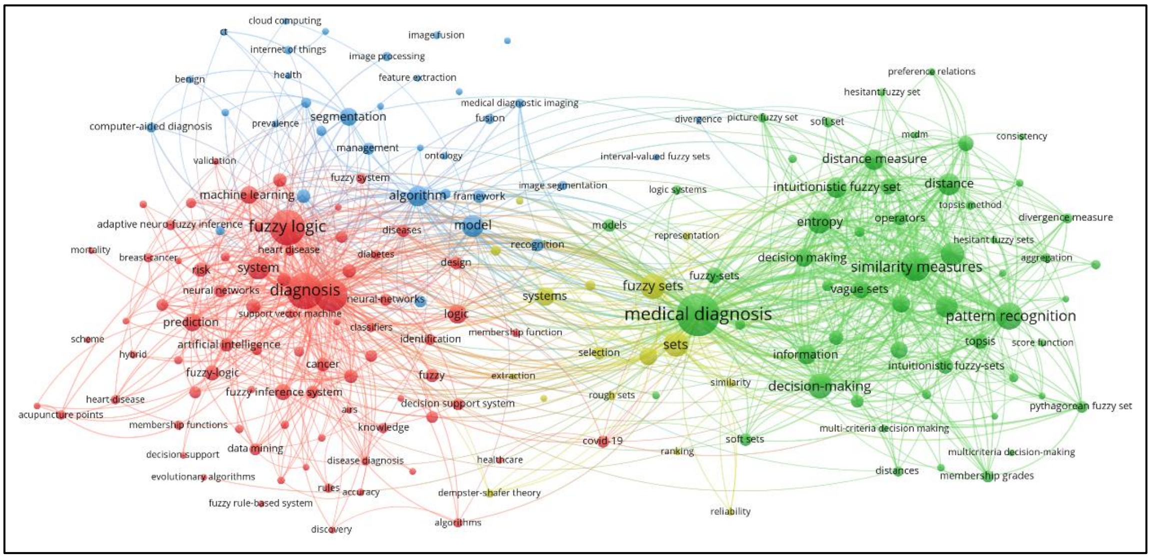

Fig. 10: All keywords co-occurrence analysis

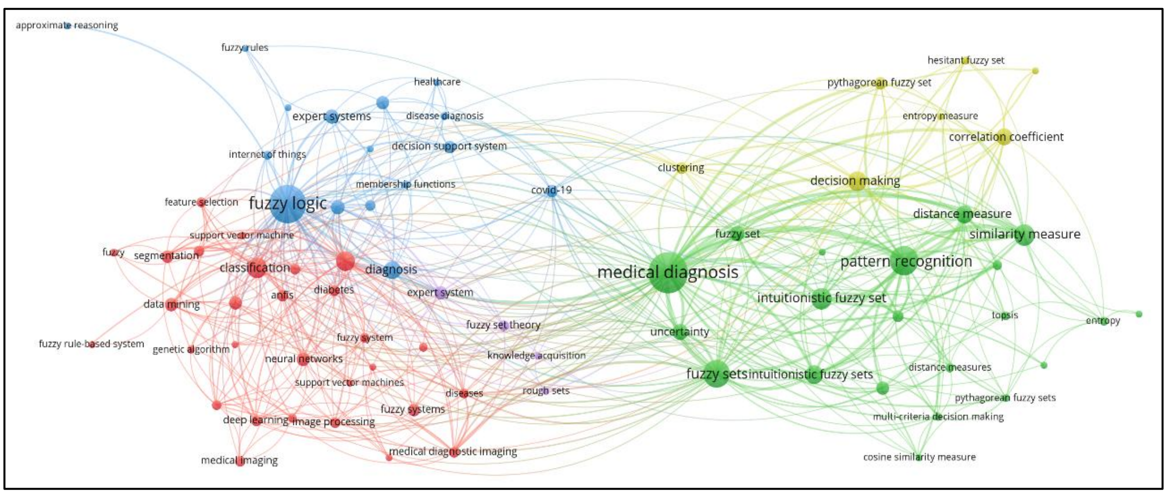

Fig. 11: Author keywords co-occurrence analysis

4 EXTENSIVE REVIEW OF FUZZY APPROACHES APPLIED TO VARIOUS TYPES OF MEDICAL DIAGNOSIS

This section extensively discusses the literature on fuzzy techniques in the diagnosis of various medical issues. We have identified five major areas of medical diagnosis, such as Chronic & lifestyle-based diseases, neurological and mental health, immunity and cancer diagnosis, pediatric and nutritional disorders, and critical care and diagnostics. These are further sub-classified into individual problems and discussed with reference to the fuzzy techniques used in them. Fig. 12 shows the detailed taxonomy of medical diagnosis problems.

4.1 Fuzzy techniques in detecting diabetes and its stages

The available healthcare frameworks are not immaculate in separating data for patients. These frameworks prescribe diets to patients without knowing the clinical history of the patients. A significant challenge in diabetes

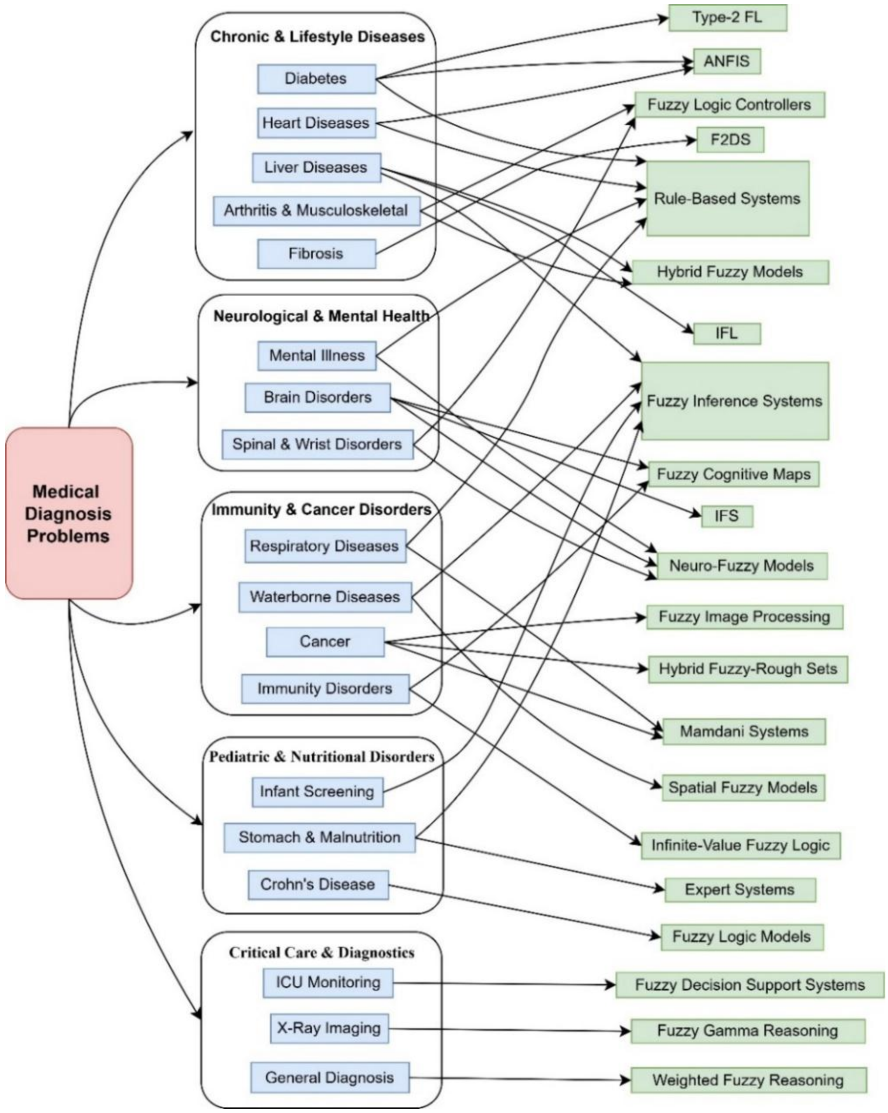

Fig. 12: Taxonomy of medical diagnosis problems and fuzzy techniques

diagnosis is managing the inherent uncertainties in patient-reported data and clinical measurements. The variability in symptoms and disease progression across individuals further complicates accurate detection and management. Because of this wastefulness, wearable sensors with T2 fuzzy inference were devised to screen the body of the patient [71]. The benefit of building these sensors was to conveniently endorse the eating routine or medications to envision the complexities of diabetes and, thus, these sensors also recommend remedies for diabetic patients. However, as the clinical information had a small sample size with high uncertainty, a T2 fuzzy regression model was employed to understand the connection between the factors and the outcome in clinical decision-making [139]. This strategy was utilized along with T2 fuzzy time series ideas to estimate neuropathy in diabetic patients. The reason for employing fuzzy techniques is their ability to model imprecise information effectively to cater to individual patient needs, especially for neuropathy. Katigari et al. [138] devised a novel framework where the boundaries were distinguished utilizing the previous information. Additionally, records were identified with patients, who were fundamentally prone to have diabetic neuropathy. These records were analyzed to assess the sensitivity, specificity, and accuracy of the developed fuzzy expert system, which plotted the trajectory of the disease. Since one ailment can give rise to another, a framework that could foresee the development of the disease at the beginning phase would be very advantageous. Following the same idea, a framework was built that took client inputs, passed it to inference engine and provided an outcome on the kind of diabetes types that was likely to develop such as type-1, type-2, pre-diabetes, and gestational [85]. The model kept an eye on the selected patients and provided precision results. It should be noted that the measurements of insulin must be exact to treat this metabolic ailment. The day by day doses of insulin couldn't generally carry a patient to a "normoglycaemic" condition. Along these lines, Grant [110] proposed a new approach which utilized insulin pumps and the theory of fuzzy logic approaches to create artificial pancreas for diabetic patients. The aim behind these systems is to improve patient outcomes by reducing manual errors in insulin dosage and automating glucose regulation.

Kakulapati et al. employed "Fuzzy-Based Predictive Analytics for Early Detection of Diabetes" to enhance the diagnostic process [207], meticulously accounting for symptomatic trends and daily routines of individuals. Hypertension is one of the significant risk factors and the reason for the development of diabetes over an extended time. The different phases of hypertension and diabetes must be investigated to understand the ailment that is likely to develop and its necessary treatment. Subsequently, it would be beneficial to build up a device that could provide a warning when glucose levels become uneven. Authors of [6] introduced a framework utilizing the adaptive neuro-fuzzy inference system (ANFIS) classifier to discern diabetes on eight features. They also used a neural network for correlation and comparison, where the ANFIS classifier performed better. The challenge of monitoring dynamic health metrics like blood pressure and glucose levels in real time underlines the need for robust systems capable of continuous and accurate evaluation, leading to the use of adaptive fuzzy logic models to manage such multifactorial risks effectively. Another unique challenge is the co-occurrence of comorbid conditions like hypertension, which can obscure early signs of diabetes. The need for early and precise detection necessitates the development of frameworks that integrate various health parameters.

4.2 Fuzzy techniques in detecting cancer and its types

Cancer is a serious disease and its identification in the early stages is significant for the treatment of the patient. One of the key challenges in cancer detection is managing the inherent uncertainty in imaging modalities and the variability in how different cancers present themselves in patients. Accurate detection requires tools that can handle noise and ambiguity effectively. Ultrasound (US) has proven to be a significant technique in classifying breast lesions, though, due to the uncertainty in US images there is a high likelihood of inaccurate diagnosis. To overcome this, Guo et al. [46] utilized the potential of standard fuzzy logic to enrich the analysis of US images. They proposed an algorithm that utilized the local and global information. This approach normalizes the image and afterwards fuzzifies it, depending on the maximum entropy principle. Hassanien proposed a study on breast cancer detection, utilizing a hybrid approach that combines the capabilities of both FSs and rough sets with statistical feature extraction [208]. Employing methods such as fuzzy image processing and the gray-level co-occurrence matrix, and then integrating rough sets for reduct generation, they notably achieved an accuracy surpassing 98% in differentiating between cancerous and non-cancerous images. The motivation for the use of these approaches lies in the need for systems that can enhance diagnostic accuracy, especially in the early stages when treatment is most effective.

Kempowsky-Hamon et al. [52] proposed a novel tool based on fuzzy logic selection to classify gene signatures with better reliability. They basically used the membership-based gene selection approach comprising the steps of gene fuzzification and membership margin-based attribute selection which simultaneously measures the contribution of multiple genes in each class. Further, class prediction was achieved with the learning algorithm for multivariable data analysis to generate fuzzy partition. A significant challenge here is the complexity of genetic data and the need for reliable techniques to interpret and classify gene expression patterns. It is essential to enable more personalized and precise cancer diagnostics. Mammography is another dependable strategy utilized for early identification of breast malignancy. However, the low contrast around breast cancer and uncertain behavior of the mammograms complicates the process of cancer detection. Thus, Cheng and Xu [104] proposed an adaptive fuzzy contrast enhancement approach to enrich the mammographic features. Their approach diminishes the noisy information in the mammograms and further utilizes fuzzy entropy rule for fuzzification. Sizilio et al. [137] assisted with the approach of fine needle aspirate (FNA) for early breast detection with the help of fuzzy logic. FNA with visual interpretation is used to the determine the growth of breast cancer. Generally, the accuracy of FNA fluctuates from 65% to 98%. To deal with such variability, the authors introduced fuzzy rule-based approach which enabled a greater accuracy of 98%. The framework improved breast cancer diagnosis to 98.59% sensitivity. The challenge in using mammography and FNA lies in the variability across imaging techniques and datasets, which necessitates robust models like fuzzy systems for enhancing feature clarity and diagnostic precision.

Yilmaz and Ayan [49] examined the contribution of stress in cancer development. They proposed a novel Mamdani-based fuzzy system for early detection of cancer and tested the model on three types of cancers such as breast, lung and colon. The datasets from the local oncology services were obtained and presented in the paper. Polat et al. [41] proposed the fuzzy logic variant for the resource allocation mechanism of Artificial Immune Recognition System (AIRS). This Fuzzy-AIRS framework was utilized as a classifier in the analysis of breast cancer and liver disorders, which are critical for proper medication. The datasets taken from the University of California at Irvine Machine Learning Repository were utilized with a 10-fold strategy. The motivation for these systems stems from the need for adaptable frameworks capable of handling heterogeneous datasets across cancer types. To deal with uncertainties in identification of lung malignancy, Schneider et al. [118] built a framework that would improve symptomatic effectiveness if there is an occurrence of lung disease. A fuzzy rule-based system was utilized that gave acceptable outcomes in 81% of the cases. For early prediction of lung cancer Yılmaz et al. [134] proposed a neuro-fuzzy inference model to identify cancer and provide primary conclusions. Significant results were achieved with an accuracy of 85%. The challenge in lung cancer detection arises from subtle differences in early symptoms and imaging features, which require intelligent models to identify at-risk patients effectively.

To deal with imprecise classification of bladder cancer patients, a model was built that dealt with T2 fuzzy inference and Cox modeling ~~naturally~~ [132]. A limit value is chosen and if the individual passes that threshold value the individual is ordered in high-risk space and the other way around. Changes in miRNA play a crucial role in the advancement of numerous diseases, including colorectal cancer (CRC). Vineetha et al. [135] applied TSK-type recurrent neural fuzzy network (TRNFN) to deduce miRNA-mRNA association network and accomplished an improved performance. FS hypotheses have likewise been utilized to deal with malignant growths in the prostate. Scrobotă et al. [61] utilized fuzzy inference to evaluate the cancer risk corresponding to oxidative stress. The serum of 16 patients were utilized as sources of input and linguistic rules were created to deliver an output. Further, to manage susceptibility to oral pre-cancer growth and disease, Banerjee et al. [88] applied fuzzy inference accord approach to the Indian populace experiencing the infection or those at risk. The information collected was separated into various age-groups and fuzzy membership was applied. Additionally, authors proposed the approach for susceptibility to oral pre-cancer by considering a fuzzy rule base and utilized Jaccard list to forecast the result. The motivation was to integrate clinical, genetic, and demographic data to offer more holistic insights into cancer risks.

Schneider et al. [120] built a fuzzy inference rule-based framework utilizing a tumor marker board that checked the degree of tumor which prompts lung disease. The authors of [64] explored the fuzzy k-nearest neighbor (FK-NN) classifier as a strategy that gave an assured prognostic and further calculated the possibility of a relapse as a statistical method and multilayer feedforward backpropagation neural networks as an Artificial Neural Network (ANN), the last two methods having been generally utilized for oncological guess. The challenge remains in balancing model complexity with real-world usability in clinical workflows, leading to the development of interpretable and efficient FISs.

4.3 Fuzzy techniques in medicine classification, bio informatics, HIV AIDS and Anesthetics

Fuzzy inferences and hypotheses have additionally been utilized in both western and eastern systems of medicine [21]. A fuzzy expert system has been built for syndromes differentiation in oriental traditional medicine, which assisted with classifying disease as indicated by the symptoms and conditions of the patient. A key challenge in this domain is the variability and subjectivity in symptom presentation, particularly in traditional medicine, which relies heavily on qualitative assessments. The motivation behind applying fuzzy systems to traditional medicine is their ability to harmonize subjective data and offer structured, interpretable outputs**.** Fuzzy sets have likewise been utilized to group ailments and inferred theories (causes) [29]. Toward the end of this inductive strategy, a single factor is identified that closely resembles the disease. Fuzzy sets have additionally been utilized to settle complex genotype and phenotype relations. The authors of [31] and [37] introduced a multivariate methodology called grade of membership (GoM) to manage the investigation of uncommon issues. This was a valuable method to distinguish important information from large volume of data. To perform delineations on medication, the authors of [39] extensively studied clinical works which utilized fuzzy inference. They performed geometrical interpretations on fuzzy sets and gave two delineations in medication and in bioinformatics. The challenge here lies in the complexity and volume of biomedical data, which can be noisy and incomplete. Fuzzy systems help bridge these gaps by offering approximate reasoning and robust decision-making capabilities**.** Medication is hard to prescribe because of the measure of information and snappy translations, thus, computational knowledge approaches like fuzzy systems are utilized to manage this issue [95]. This strategy has assisted with creating efficient models in healthcare, medication and bioinformatics. The motivation for these systems is the need for scalable, adaptive methods to process diverse medical datasets and support decision-making in real time. Accuracy in the dynamic field of bio-informatics is very difficult on the ground that various illnesses are either incomplete or imprecise as information is gathered from various sorts of clinical gear. Fuzzy inference and speculations have been used in prescribing prescriptions to fundamentally sick patients [40]. Merouani et al. [43] utilized fuzzy logic to lessen the shock duration and prescribe medication to septic patients. A key challenge here is the urgency and precision required in critical care settings, where decisions must be made rapidly with incomplete information. Fuzzy models excel in such environments by balancing speed and reliability.

The U.S. health department changes their HIV/AIDS treatment guidelines frequently because of the fast developments in the clinical field. Thus, Ying et al. [44] studied a self-learning selection system for HIV management protocol based on the fuzzy discrete event system (FDES), that gave a precision between 84.4-100%. This framework could comprehend one of the most successful treatments in healthcare. The challenge in HIV management lies in its ever-evolving treatment protocols and patient-specific factors, necessitating adaptive systems that can keep pace with medical advancements. The motivation for using fuzzy systems in this context is their capacity to dynamically learn and adapt to new guidelines and individual patient needs. Since uncertainty is indivisible from clinical science, fuzzy inference strategies have been utilized to deal with vagueness to a huge degree. Ahsan and colleagues introduced the Complex Fuzzy Hypersoft (CFHS) set in their model to handle ambiguity in HIV data [209]. Utilizing CFHS's distinctive properties, they have addressed difficulties in identifying HIV and gauging its severity. A unique challenge in HIV diagnostics is the ambiguity in the early symptoms and the variability in viral progression among individuals. The motivation for the use of CFHS systems lies in their ability to model these uncertainties and deliver actionable insights. FSs also have an application in life sciences [45]. Fuzzy control system has additionally been utilized as controllers in sedatives in [48], and [50] to help to decide on how best to react to, conditions such as low blood pressure, tachypnea, or decreased oxygen saturation. Further, a self-learning FIS was created for medicines by Mason et al. [56]. To estimate the desired fluid infusion rate for a particular patient, a decision support system (DSS) was proposed that utilized the fuzzy inference control unit [57]. Authors of [51] and [53] also utilized the fuzzy system model for clinical findings for different illnesses. The motivation here lay in the necessity for precision and adaptability in drug administration, particularly in critical care scenarios where individualized treatment plans are paramount. Aggregating a state space view of an animal and its variable with representation using the FSs leads to a fuzzy systems model, which can effectively analyse illnesses. The FSs-based approach has advantages that are inaccessible in other techniques. For computational portrayal of clinical ideas, the authors of [54] proposed an FIS, which along with semiotic techniques explicitly showed two significant attributes such as imprecision and context-dependency. A similar methodology has likewise been utilized by experts to build up a framework to direct the power of physical activity among youngsters [59]. Brain cooling is a significant strategy in medication to evade strokes. In this regard, Yavuz [60] designed a protective cap to cool the brain whose viability was tested using FIS. It proved favorable as it promised to protect neurons and rapidly cool the brain. Traulsen and Krieter [136] studied the modelling capabilities of fuzzy logic for linguistic variables. A thorough examination was made with Gaussian distribution and fuzzy inference models, where the precision resulted somewhere in the range of 87.0% and 99.9%. Helmy et al. [198] proposed a versatile T2 Fuzzy Logic System (FLS)-based classification framework for multivariate data to analyse various sorts of diseases. This structure could deal with imprecision and uncertainty, and its classification precision and accuracy were estimated by utilizing the University of California Irvine (UCI) repository. Boegl et al. [42] proposed the fuzzy knowledge representation approach of the framework named MedFrame/CADIAG-IV. Alongside, they studied knowledge acquisition approaches of knowledge concepts and inference rules. As in previous CADIAG-II, fuzzy clinical databases were utilized to show the ambiguity of clinical ideas and fuzzy logic reasoning mechanism which resulted in standard inference procedures. Table 2 summarizes the above discussion in the three sections (4.1-4.3).

Table 2: Related research for fuzzy approaches in diabetes, cancer, medicine classification, bio informatics, HIV AIDS and Anesthetics

Fuzzy Approaches	Medical Diagnosis/Medical Applications	References
T2 fuzzy inference, T2 fuzzy regression model, T2 fuzzy time series	Wearable sensors for patient monitoring, estimating neuropathy	[71], [139], [138]
Fuzzy inference system	Diabetes classification, Device for glucose level imbalance detection	[85]
Fuzzy logic control, ANFIS classifier	Diabetes classification	[110]
FL, FIS	Breast cancer detection, classify gene signatures	[46], [52]
Fuzzy entropy rule	Reducing noise in mammograms	[104]
Fuzzy inference engine	Cancer risk assessment, Pre-diagnosis	[49]
Fuzzy-Logic classifier	Diagnosis of Breast Cancer, Liver Disorders	[41]
FRBS, Neuro-fuzzy inference model	Diagnostic efficiency, Risk prediction & pre-diagnosis in lung cancer	[118], [134]
T2 fuzzy inference and Cox modeling, TSK-type recurrent neural network, Fuzzy inference, FK-NN	Classification of bladder cancer patients, miRNA identification in CRC	[132], [135], [61], [64]
Fuzzy inference consensus approach, Fuzzy inference rule-based system	Susceptibility to oral pre-cancer, Tumor marker-based lung cancer detection	[88], [120]
Fuzzy logic, theory and inference system	Syndromes differentiation in oriental medicine, disease classification & genotyping, Complex genotype & phenotype relations, Medical literature review, prescription recommendation for critical patients, Septic patients	[21], [29], [31], [37], [40], [45]
Fuzzy systems	Healthcare, medicine, and bioinformatics	[95]
FDES	Self-learning selection system for HIV management protocol	[44]
Type-2 FLS	Multivariate data for disease diagnosis	[198]

4.4 Fuzzy logic techniques to find out patterns in medical datasets, Amino acids and Leukocyte in blood

A combination of T2 FSs and refined fuzzy methodology was utilized to obtain a superior image of amino acid patterns in clinical datasets [66]. One of the key challenges in analyzing clinical datasets is the presence of noise and biases in datasets with high dimensionality or incomplete information. T2 FSs can handle this higher-order uncertainty more effectively than traditional T1 FSs. Since T1 FSs could not remove biasness from the dataset, the authors used T2 FSs to address this issue. Chen et al. [67] proposed an extended QUALIFLEX approach for the problems of multi-criteria decision making, using interval T2 FSs (IT2 FSs). This approach explores every single imaginable option in the choices for a degree of concordance of the complete preference order. The challenge here lies in balancing multiple conflicting criteria in medical decision-making, where precise solutions are often infeasible. IT2 FSs provide flexibility in modeling preferences and trade-offs in uncertain environments**.** A novel Attanassov intuitionistic fuzzy set (IFS)-based approach for blood vessels and blood cells in pathological images segmentation was proposed by Chaira [69], who also in [68] utilized IFS and T2 FS for precise segmentation of leukocyte in blood cell images. Also, an improved version of Cauchy distribution was presented. Experimental results validate the effectiveness of IFS and T2 FSs over traditional FSs. The challenge in pathological image segmentation lies in identifying subtle features within noisy and overlapping image data. Employing IFS and T2 FS together can provide robustness in preserving accuracy under such conditions. Gaweda et al. [128] exhibited how FSs can be utilized in a pharmacodynamics model to address the uncertainty about the progression of a disease. The forecast was performed by a weighted linear combination of past haemoglobin, transferrin saturation, and erythropoietin dose. Pharmacodynamics faces challenges in the integration of diverse biomarkers with varying levels of reliability. Fuzzy approaches have the ability to aggregate uncertain inputs into meaningful predictions for treatment optimization.

Satpathy et al. [152] introduced a novel strategy with the assistance of fuzzy and FPGA-based framework for forecasting different illnesses in a provincial region. The development lay in a low force FPGA and fuzzy set-based strategy for identification and prediction of four fatal diseases like jaundice, diabetes mellitus, yellow fever, and cholera. One challenge is the lack of computational infrastructure in rural regions, making resource-efficient systems critical. FSs with FPGA has the potential to create low-power, cost-effective diagnostic tools suitable for such environments. Sanchez [186] developed a model for handling marginal cases to enable patient analysis using FSs-based pattern matching. To address poor diagnostic grouping, weights were adjusted for certain signs so as to refine syndrome classification to better align with better diagnosis. Here, the challenge in diagnosing marginal cases lay in managing overlapping symptomologies and weak signals. FSs-based models adapt conveniently in weighting and revising classifications to improve accuracy. Ye et al. [196] proposed a novel methodology dependent on an adaptive neuro-fuzzy inference system (ANFIS) to define a patient with neurodegenerative (ND). The proposed ANFIS model consolidated neural network versatile capabilities and the qualitative approach of fuzzy logic. The model took input variables such as, stance, stride, and double support intervals and used particle swarm optimization (PSO) to identify the parameters of the ANFIS model. The challenge in gait analysis for ND patients is in the variability of movement patterns and the lack of standardized diagnostic tools. ANFIS and PSO can efficiently integrate adaptive learning with imprecise reasoning, enabling personalized insights**.** Nguyen et al. proposed the GSAM approach, which integrates the fuzzy standard additive model with a genetic algorithm, to address the uncertainty and computational challenges inherent in healthcare data [210]. By utilizing wavelet transformation for feature extraction and evolving rule optimization through GA, GSAM adeptly manages high-dimensional medical datasets, demonstrating superior performance in classifying health conditions. The challenge in managing high-dimensional medical data is the risk of overfitting and computational inefficiency. GSAM's hybrid approach combines the interpretability of fuzzy models with the optimization strengths of GAs.

4.5 Fuzzy techniques used to classify heart diseases and medical images

Watanabe [28] applied ideas from FST to cases of valvular heart diseases. The method included two sections such as discrimination and connectivity analysis, using the prototypicalness of patients to improve the efficiency of the diagnosis and achieved the 81% accurate diagnosis. Srinivas et al. [30] developed an integrated rough set and FST classifier together for the prediction of heart disease. Two major steps were followed such as rule generation using rough set theory, and then prediction with the fuzzy classifier. The approach achieved an accuracy of 80% and 42% in the datasets from Switzerland and Hungry, respectively. The authors of [35] proposed a mediative fuzzy ~~inference~~ system that depends on the principles of fuzzy logic. It is an extension to the Mamdani inference system (MIS) designed to diagnose heart disease. Sanz et al. [72] built a classifier to decode if a patient could develop a cardiovascular disease within the next ten years. This framework provided diagnosis as well as the corresponding model explanation, combining the fuzzy rule-based classification systems with interval-valued FSs (IV FSs). Further, Chaira [74] worked on the enhancement of edges in medical images using IFSs. The IF entropy was utilized to identify membership and non-membership functions. On comparing non-fuzzy and fuzzy approaches, it gave better outcomes and handled uncertainty efficiently with better diagnosis. One of the prime challenges in diagnosing heart diseases is the variability of clinical presentations, where symptoms often overlap with other conditions. For example, arrhythmias and coronary artery disease may exhibit subtle differences in ECG signals that are difficult to detect using traditional methods. Additionally, the limited availability of labeled data increases the complexity of developing accurate classifiers. Applying fuzzy logic to heart disease diagnosis stems from its ability to handle imprecise, and uncertain data. Fuzzy models excel at integrating diverse clinical parameters to provide interpretable and robust predictions. The ultimate goal is to improve early detection and personalized treatment plans, which are critical for reducing mortality and morbidity associated with cardiovascular diseases.

Das et al. [77] introduced a novel approach to provide health care support to people living in the distant rural area and termed the approach medical diagnostic support system (MDSS), which used a knowledge base (KB) and an intuitionistic fuzzy inference system (IFIS). The human eye is an incredibly sensitive organ with delicate nerves, thus, Mookiah et al. [78] proposed a novel approach utilizing Attanassov intuitionistic fuzzy histon (A-IFSH)-based segmentation to recognize the optic disk (OD) in retinal fundus images. The outcomes demonstrated the prevalence of proposed fuzzy segmentation procedure over different techniques. The authors of [93,97] proposed a specialized framework called CADIAG-2 for clinical analysis in the field of internal medicine. Based on FST, the authors provided a probabilistic formalization of the inference mechanism and validated its effectiveness using probabilistic inferences. They described models that provided knowledge to the different parts of CADIAG-2 [97], and mentioned about three diverse conventional frameworks, based on t-norm, probability theory and possibilistic logic.

An automated heartbeat classification approach using an electrocardiogram is crucial in assisting medical physicians to diagnose cardiovascular diseases. Lee et al. [101] proposed a novel approach, dependent on a local transform pattern (LTP) with a hybrid neural fuzzy inference system and a self-organizing map. Various feature extraction approaches were used to extract a histogram feature with multi-dimensions. Test results showed the efficiency of the proposed approach with sensitivity, predictivity, false positive rate, and accuracy of 87%, 73.8%, 1.1%, and 98.84%, respectively. Helgason and Jobe [111] affirmed that the fuzzy logic better handles clinical uncertainty in cerebrovascular disease as compared to the current probability theory-based technique. Though different traditional statistical methods were used, fuzzy logic-based paradigms gave better precision. Heart disease prediction systems face significant challenges, including the integration of heterogeneous data types (e.g., ECG signals, patient histories) and the need for real-time analysis in clinical settings. Noise and artifacts in ECG data further complicate the task, as they may obscure critical features required for accurate classification. Fuzzy systems have the ability to handle such noises while extracting meaningful patterns. These methods enable clinicians to make reliable decisions, even in resource-constrained environments or emergency scenarios.

Liu et al. [124] built a fuzzy logic discriminator to consider the peaks of PPG signals for heart monitoring which allowed for reliable monitoring of a patient's physiological levels during the fast pulse changes. In [125], ANFIS was introduced for the identification of ophthalmic artery stenosis. This model had the advantage of merging neural network adaptive abilities with the qualitative approach of fuzzy logic. The performances of the ANFIS was evaluated in terms of training performance and classification accuracies, where the results confirmed that the ANFIS classifier had the potential to detect ophthalmic artery stenosis. In order to detect heart diseases, Reddy and

Khare [126] developed an oppositional based learning (OBL) with BAT and rule-based fuzzy logic (RBFL). This novel approach helped doctors to automate heart diagnosis and improve medical care for the patient. The authors of [24] proposed a novel fuzzy-evidential hybrid inference engine that used the Dempster–Shafer theory of evidence and FST. In its first phase, information is modelled using FSs to handle vagueness, then the rules are extracted and the fuzzy inference engine is used to get the results for the level of risks of coronary disease. The hybrid model gave accurate results so as it can be considered as an intelligent system. Anderson et al. [34] proposed a learning algorithm to adjust the MFs. The method is applied to the POSCH problem to calculate the risk of coronary artery disease. The proposed rough/fuzzy set method correctly predicted the progression of disease in 69% of the patients, which is statistically better than neural networks, rough sets and logistic models. Coutinho et al. [144] developed a system to predict the hospitalization time of cardiovascular disease patients. The output variable of the system is the average length of hospitalization with six MFs. This model was built using the MATLAB toolbox and the accuracy was assessed with the ROC curve. Korkmaz et al. [151] evaluated the cardiac score of the Turkish population by using the MAMDANI inference engine which also gave a detailed review of the metabolic syndrome in patients and techniques to reduce it. The results show that the proposed system was able to evaluate the Metabolic Syndrome risk with 0.9285 specificity, 0.92708 accuracy and 0.925 sensitivity. Patients generally express problems in words and to handle word uncertainties, HMT Per-C was proposed [160]. The model used perceptual computing with IT2 FSs to handle the risk of heart failure in patients. The authors compared the above approach with the extension principle, symbolic method and 2-tuple. The results were promising in this approach. A Mamdani-based fuzzy linguistic model [144] was proposed with input factors like particulate matter, sulfur dioxide, temperature, and wind from CETESB to predict hospitalization time for cardiovascular diseases. The model's predictions, compared to real data with 0 to 4-day lags, showed significant accuracy in terms of the ROC curve.

The Artificial Immune Recognition System (AIRS) [168] has indicated a strong performance on AI benchmark issues, clinical ~~arrangement~~ issues like breast cancer, diabetes, and liver issues classification. In this examination, the resource allocation mechanism of AIRS was changed by fuzzy logic. This framework, called Fuzzy-AIRS, was utilized as a classifier in the determination of atherosclerosis, which is critical in medication. Results depicted that the Fuzzy-AIRS could be utilized as a viable classifier for clinical issues. Ramirez et al. [185] built an insightful model using fuzzy logic and neural networks where T1 and T2 FIS were used with the MIT-BIH arrhythmia database. The best order rate results were acquired utilizing IT2 FIS rather than T1 FIS. Al-Kasasbeh et al. [200] proposed a scientific model for the collaboration of the internal and natural dynamic points of meridian structures. The investigation of these models permits the particulars of a rundown of heart illnesses for which reflex diagnostics and reflex therapy techniques are best and furthermore permits expanding the adequacy of these systems. Acceptable outcomes for the forecast and early finding of disease from the reaction energy of acupuncture points were also acquired utilizing fuzzy logic approaches. A novel image segmentation technique utilizing IFS and a new MF was proposed by Chaira [73]. An intuitionistic fuzzy image is built utilizing Sugeno type intuitionistic fuzzy generator. The use of δ-equality are critical to fuzzy measurements and fuzzy reasoning. A few attributes of δ-equality that were also talked about in the past were also examined. Authors of [75] applied the δ-equalities to clinical analyses to examine a patient's infections as side effects. The aim was to utilize δ-equality for intuitionistic fuzzy relations to discover gatherings of intuitionistic fuzzified sets with certain correspondence or similarity degrees joining them at that point. The authors of [79] used fuzzy clustering to detect high-grade CAD in patients with mild degrees of ST segment depression. Combining stress test variables by fuzzy cluster analysis can be useful in managing patients with positive exercise test results. Authors of [112] utilized many three differential equations as a dynamic model of ECG signals. They dissected the progressions that occurred in the ECG model parameters because of arrhythmias. Two classifiers were built to arrange ECG signals as indicated by the parameter changes. Classifiers can identify similarities among ECGs and isolate them utilizing these similarities. The authors can forecast the state of the heart through clinically acquired ECGs all the more correctly through these classifiers.

Reddy et al. [211] developed an adaptive GA with a fuzzy logic (AGAFL) model, aimed at early heart disease prediction. Employing rough set theory for feature selection followed by an AGAFL hybrid classifier, their approach demonstrated superior diagnostic accuracy compared to existing models on UCI heart disease datasets. Authors of [223] proposed a fuzzy logic-based artificial intelligence system, integrated with IoT, designed for health monitoring and diagnosis, specifically targeting cardiac arrhythmia in critical COVID-19 patients. The system used ECG data from the MIT-BIH database for training and achieved approximately 100% accuracy in real-time validation. Table 3 summarizes the above discussion in the sections about fuzzy approaches in amino acid, leukocyte in blood, medical images, and heart disease.

Table 3: Summarizing related research for fuzzy approaches in amino acid, leukocyte in blood, medical images & heart disease

Fuzzy Approaches	Medical Diagnosis/Medical Applications	References
T2 FSs, IT2 FSs	Amino acids patterns in clinical datasets, Multi-criteria decision making	[66], [67]
IT2 FSs, Attanassov IFS	Blood vessels and blood cells segmentation, Leukocyte segmentation, Enhancement of edges in medical images	[68], [69], [74]
Fuzzy sets and FPGA-based system	Pharmacodynamics model, Forecasting the progression of a disease, and different illnesses in a regional area	[128], [152]
Fuzzy sets for processing marginal cases	Processing marginal cases, Diagnosis assignment based on FSs	[186]
ANFIS, PSO	Distinguishing gait of patients with ND illness	[196]
Fuzzy SAM with GA	Handling uncertainty and computational challenges in healthcare data	[210]
Fuzzy set theory	Determination of valvular heart disease, Clinical diagnosis in internal medicine	[28], [93, 97]
Rough fuzzy classifier, rough set and FST	Prediction of heart disease	[30]
Mediative fuzzy inference framework	Heart disease diagnosis	[35]
FRB classification systems with IV FSs	Determining the risk of cardiovascular disease	[72]
IFIS	MDSS	[77]
A-IFSH	OD detection in retinal fundus images	[78]
Hybrid neural FIS w/h self-organizing	Automated heartbeat classification	[101]
Fuzzy logic related approaches	Clinical unpredictability in cerebrovascular disease, Prediction of hospitalization time of cardiovascular disease patients, AIRS for atherosclerosis detection, Early heart disease prediction, health	[111], [144], [168], [211], [223]
Fuzzy logic discriminator, ANFIS	PPG signals monitoring, Identification of ophthalmic artery stenosis	[124], [125]
OBL with BAT and RBFL	Automated heart diagnosis	[126]
Fuzzy-evidential hybrid FIS using Dempster–Shafer theory of evidence	Risk prediction of coronary disease	[24]
Learning algorithm to adjust FS MFs	Prediction of progression of disease in POSCH problem	[34]
MAMDANI inference engine	Prediction of hospitalization time due to cardiovascular diseases, Evaluation of heart score in Turkish population	[144], [151]
Perceptual computing with IT2 FS	Risk of heart failure prediction	[160]
Fuzzy logic and NNs, T1 and T2 FIS	Diagnosis with MIT-BIH arrhythmia database	[185]
AGAFL	Collaboration of the internal & dynamic points of meridian structures	[200]

4.6 Fuzzy techniques used in detection of brain diseases.

The authors of [76] utilized the fuzzy approximate entropy and fuzzy sample entropy procedure to detect Alzheimer's disease (AD). Moreover, to distinguish between the anomaly of abnormality of irregularity and chaotic behavior in the AD brain, the complexity features dependent on these two fuzzy entropies are extricated in the delta, theta, alpha, and beta groups. The results highlighted an accuracy of 88.1%. The results demonstrated that fuzzy entropy might be an integral asset to portray the multifaceted irregular nature of AD. For a better understanding of the infection, the authors of [82] introduced an intuitionistic fuzzy cognitive map (iFCM), proposing a computer-aided diagnosis system dependent on iFCMs to decide the evaluation of celiac disease. The outcomes confirmed the capacity and viability of the model. The approach provided precision in deciding the type of a disease and furthermore got higher accuracy. To determine the type of illness the authors of [83] proposed a fuzzy probabilistic technique to appraise the likelihood of a patient having a specific ailment, which could be used in different ways to model the analytic procedure. The model held a bit of leeway over the min-max structure utilized earlier. To find a connection between manifestations and ailments, the authors of [84] proposed a framework in which their relations were depicted by IFS information. The authors outlined 4 unique measures for medical diagnosis and a model of fuzzy diagnostic sets and regression method was built with the information. This could be utilized to group a new patient's ailments with specific degrees of conviction and it's side effects. Soundrapandiyan et al. [86] proposed a discrete wavelet transform (DWT) and IFSs-based combination strategy (DWT-IFS) for the identification of tumors. At first, all source images were combined utilizing DWT with the average, maximum, and entropy fusion rules. Further the IFS processed images were changed into intuitionistic fuzzy images, and the subsequent images were disintegrated into blocks, which were intertwined utilizing the operations of IFS. The DWT-IFS fusion strategy gives higher quality of results when compared with current techniques. For automated diagnosis, a Boolean fuzzy inference system (FIS) is used to evaluate rules for disease assessment. As proposed in [87], this system helps patients estimate disease likelihood and suggests prompt treatment when medical experts are unavailable.

Knowledge-based systems (KBS) and intelligent systems have been utilized in clinical arranging, determination and treatment. The authors of [94] made an investigation of a variety of singular and joined techniques (185 in number), appropriate to the clinical area for grouping of infections. It was apparent that the techniques utilized in clinical determination not many were used to arrange and moderate the number in treatment. An DSS based on fuzzy inference has been attracting in specialists as it handles uncertainty well. The authors of [98] utilized soft computing (SC) techniques with fuzzy inference. The primary point was to have an investigation of different SC systems with its application in clinical science. The authors of [99], proposed a novel framework utilizing fuzzy inference and recurrent neural networks for definition and to gauge a patient's clinical condition by utilizing five clinical boundaries. Because of this, a fuzzy model and six ANNs were tried and experimented with. It was found that the fuzzy Nonlinear Autoregressive with eXogenous inputs (NARX) provided high precision. More tests made with higher forecast periods show a slight reduction in the results. Because of the absence of search techniques, the utilization of online clinical images was constrained. Accordingly, Atque and Bhagat [100] proposed two strategies; fuzzy connectedness image segmentation with geometric moments (FCISGMs), and localized entropy-based medical image retrieval (LEBIR) for recovery of digital imaging and communications in medical pictures, which showed better accuracy and recall. The authors of [102] proposed a strategy for segmenting a magnetic resonance (MR) picture of a human brain based on fuzzy inference. For the most part, histograms of MR volumetric images change from individual to individual. A segmentation experimentation was conducted on 50 human brain MR volumes, whose outcome recognized the entire mind with a decent precision.

To manage uncertainty and computational difficulties in healthcare, Nguyen et al. [105] proposed a fuzzy standard additive model (SAM) with GA, called GSAM. GSAM includes three stages: rule initialization, evolutionary rule optimization, and parameter tuning utilizing adaptive vector quantization clustering, GA and the gradient descent, respectively. Fuzzy inference is a ground-breaking and crucial tool for dealing with intricate issues under inadequate information conditions. To deal with inadequate clinical information, Khashei et al. [114], proposed a mixture model that consolidates ANN with fuzzy. The proposed model, because it utilized the fuzzy boundaries rather than non-fuzzy boundaries required less data as compared to conventional non-fuzzy neural networks. Fuzzy frameworks perform a vital job in handling ambiguity and uncertainty in DSS. In this way, the authors of [121] proposed a fuzzy expert system that could suggest suitable care for incessant diseases. The authors utilized expert judgment on cases and direct estimates by specialists, to enhance aggregation operators and treat heterogeneous mixes of combination. Parkinson's disease is a severe ailment in which patients shows numerous manifestations of which tumor is the primary one. Accordingly, the authors of [123] built a FIS, which would modify the stimulation to the various conditions of the patient. The point of the framework was to choose whether incitement was required by the patient. Finally, a FIS was applied to the created framework which brought about high accuracy of 98.7 % in 70 % of the patients.

AD is a basic type of dementia and cannot be reserved, therefore it is imperative to analyse AD as early as could be expected under the circumstances. Tangaro et al. [133] proposed a framework involving advanced fuzzy classification and trained Support Vector Machine (SVM) classifiers for each class using cognitive and morphometric measurements of healthy and Alzheimer's disease (AD) patients, achieving an accuracy of 88.2%. The authors of [141] built a framework to distinguish anatomical targets, which were found inside the brain. They built up a semi-automated technique for image examination, in view of data fusion. Data from both anatomical targets and specialists was utilized to ~~in~~ a common possibilistic frame, utilizing a fuzzy inference approach, resulting in better results. The authors of [146], built up a versatile fuzzy rule base (FRB) framework that was applied on ~~genuine~~ MR images for putamen segmentation. The FRB framework gave better execution, since putamen region is firmly identified with neurological infections. The authors of [155], devised an AI strategy both on ~~measurements and~~ fuzzy inference on ~~cerebrum~~ MRI features so as to check the working of the brain. This model presented significant level of exactness (89.1%), especially high affectability (93.8%) and agreeable negative predictive value (81.5%) and positive predictive value (91.6%). The authors of [36], built a framework utilizing fuzzy connectedness delineation to deal with the obstacles that exist in organ with seed points. By and large, the delineation accuracy is 0.34% (false positive) and 4.02% (false negative).

The authors of [37] explored the use of fuzzy inference in clinical sciences and its potential for future applications, signifying its ability to summarize and extract relevant facts from large datasets. The authors of [38] proposed an expert system to assess sleep disorders, using fuzzy inference to match symptoms to diagnoses. These models, inspired by an epidemiological study in Italy, showed advantages over binary and Bayesian analysis methods. The authors of [47] focused on a variety of modes including the utilization of fuzzy and neuro-fuzzy strategies in clinical applications. The authors of [55] centered around the philosophical foundation for applying fuzzy inference to clinical hypotheses. They challenged Zadeh's unrestricted proposition for the conceptual definition of health and disease. Complex biological frameworks can be effortlessly controlled with fuzzy inference and the use of linguistic rules. Hence, the authors of [58] proposed an enzyme-free DNA strand displacement-based design of fuzzy inference engine utilizing fuzzy operators, like, fuzzy intersection and union. All these DNA circuits are actualized and reproduced in Visual DSD tool. Phuong proposed to mimic medical experts in incorporating western and eastern medication symptoms utilizing fuzzy inference [62] by presenting a model joining the various inferences of western and eastern medication in diagnosis and treatment. The side effects of Parkinson's disease can be eased through Deep Brain Stimulation.

The authors of [159] proposed the content selection methodology dependent on test connection of the curvelet transform coefficients, in which the determination of curvelet coefficients was advanced by applying weighted averaging and maximum selection rules for high frequency coefficients and calculation was assessed on an ideal brain angiography image dataset comprising one hundred 2-D internal carotid rotational angiography recordings. The authors of [179] proposed a rapid selection of patients utilizing Alzheimer Disease Identification Number (ADIN), using fuzzy logic and big data which empowered the estimation of the progression of the disease within a patient's specific circumstances. It provides adequate expressiveness in understanding the patients data and facilitating the recommendation of related treatment or the prediction of expected outcomes. The authors of [191] used Mamdani FIS for brain tumor detection. The extracted features were prepared and ordered into typical or unusual brain image by feed forward back propagation neural networks. Morphological activities were utilized to section the brain tumor from the grouped brain images. The technique introduced in this paper was tried over images accessible from the open datasets and accomplished an sensitivity rate of 99.67%, specificity rate of 99.56% and precision of 98.75%. The authors of [212] proposed a brain disease prediction model utilizing improved fuzzy clustering and HPU-Net for MRI brain image processing. Demonstrating superior performance, their algorithm achieved the highest segmentation accuracy in tests, outperforming other prominent models in speed, energy consumption, and precision. The authors of [197] centered around the patient distinguishing proof utilizing large datasets and Fuzzy Logic, which had been accomplished through fuzzy processing where a reference metric called Alzheimers Disease Identification Number (ADIN) is determined. The detection and diagnosis of brain diseases, such as Alzheimer's, Parkinson's, and brain tumors, face several challenges, including complexity of brain imaging data, which differs significantly between individuals due to anatomical and pathological diversity. Also, the high dimensionality and noise in MRI, CT, and other imaging modalities makes it difficult to extract useful features for classification and segmentation. Another challenge is the integration of clinical data with imaging results, as these often come from different sources, making the decision-making process complicated. Further, brain diseases often present subtle early-stage symptoms to make early detection difficult. To address these challenges, fuzzy techniques in brain disease detection offers the ability to handle uncertainty, ambiguity, and incomplete data. They provide a robust framework for modeling complex relationships between symptoms, imaging features, and diagnostic outcomes. Techniques like fuzzy clustering, fuzzy rule-based systems, and neuro-fuzzy models enable more accurate segmentation of brain images and the identification of critical regions affected by diseases. These approaches offer personalized diagnosis by integrating patient-specific clinical data with imaging findings. The goal is to enhance early detection, improve diagnostic precision, and provide actionable insights for timely interventions, thus, improving patient outcomes and the quality of life.

Table 4: Summarizing the related research for fuzzy approaches in detection of brain diseases

Fuzzy Approaches	Medical Diagnosis/Medical Applications	References
Fuzzy approximate entropy	Alzheimer's Disease (AD) Detection	[76]
Intuitionistic fuzzy cognitive maps (iFCM)	Celiac Disease Diagnosis	[82]
Fuzzy probabilistic method, Boolean consistent fuzzy inference system	Disease Probability Estimation, Clinical Diagnosis, Disease Assessment, Patient Identification	[83], [84], [87], [197]
DWT and IFSs based fusion strategy	Tumor Detection	[86]
Fuzzy SAM with GA	Clinical Decision Support	[105]
Hybrid model with AI and fuzzy logic	Clinical Data	[114]
Fuzzy inference system	Closed-Loop System for Parkinson's	[123]
SVM classifiers, Fuzzy logic and big data	Alzheimer's Disease Diagnosis, ADIN	[133], [179]
Semi-automated method based on fuzzy inference	Brain Anatomical Target Detection	[141]
Adaptive fuzzy rule base (FRB) system	Putamen Segmentation	[146]
Quantitative MRI features and Fuzzy Logic	Multiple Sclerosis Diagnosis	[155]
Fuzzy-based fusion scheme for curvelet coefficients	Brain Angiography Image Fusion	[159]
Mamdani FIS, Improved fuzzy clustering	Brain Tumor Detection, Brain Disease Prediction	[191], [212]
FK-NN classifier	Prognostic Decision making	[65]

The authors of [63] proposed fuzzy synchronization likelihood (SL), utilizing the hypothesis of fuzzy logic and Gaussian MFs. This fuzzy SL was compared with the traditional SL utilizing both a standard problem from the chaos literature and a neurological diagnostic problem, that is, the EEG-based diagnosis of Attention-Deficit/Hyperactivity Disorder (ADHD). The ANOVA statistical analysis demonstrate that interdependencies estimated by fuzzy SL are more reliable. The authors of [64] explored the FK-NN-classifier as a fuzzy logic strategy that gives an certainty degree to prognostic choices and an appraisal of the markers. They further compared it with: 1) logistic regression and 2) multilayer feedforward backpropagation neural networks. Table 4 concludes the above discussions in the section.

4.7 Fuzzy techniques used in classifying diseases of the liver and water borne diseases

Since fuzzy inference was developed as one of the widely-used classification tools, the authors of [107] proposed fuzzy inference methods to separate diffuse liver infections utilizing numerical quantitative features, estimated from ultrasound images. The methodology utilized had great sensitivities and specificity for classifying diffused liver pathologies. The authors of [108] provide an early warning GIS model designed to identify conditions favorable for cholera outbreaks. These conditions were analyzed using an expert support system, with the identified factors fed into a spatial fuzzy inference model to assess risk levels. Fuzzy inference methods have additionally been utilized in mass immunization battle for measles [109]. The authors of [115] demonstrated the predominance of fuzzy approaches over the traditional AHP, which were then experimented with 30 malaria patient's data. Outcomes validated the prevalence of FIS over AHP. The authors of [122] explored whether a classification technique dependent on FIS of tumor marker profiles was achievable in patients with pancreatic carcinoma and benign pancreatic sickness. Tumor markers and different parameters were tried utilizing the fuzzy inference systems which resulted in a precision of 83% when compared with older strategies. The authors of [145] utilized a FL approach to highlight environmental factors in determining dengue risk. They showed that fuzzy inference effectively handled the complexities of vector-species interactions and helped public health authorities in preventing waterborne diseases. The authors of [150] used Intuitionistic fuzzy logic (IFL) to anticipate the expense for the treatment of hepatitis patients, so as to deal with vagueness and hesitation. The authors of [153] studied a fuzzy information-based expert system to recognize the phases of liver fibrosis. Their approach explored different metrics and achieved an accuracy of 95.7%, and could assist doctors as part of a healthcare system. The authors of [213] introduced a hybrid model, hybrid modlem2-fuzzy classifier (HFMC), which utilized laplace-Modlem2 and fuzzy classifiers to enhance the accuracy of liver disease diagnoses. Utilizing rough set approaches, the model automated rule generation, achieving an impressive 99.14% classification accuracy. The authors of [158] introduced a FL based control system that was utilized to control liquid parity in kidney transplants, which when compared with operational records of kidney transplants, showcased its dominance.

The authors of [219] developed a fuzzy logic-based medical diagnostic system for Hepatitis B, utilizing machine learning techniques to enhance early detection and diagnosis of the virus. This system aims to improve accuracy and reduce the cost and complexities associated with traditional diagnostic methods. The authors of [177] proposed a fuzzy logic model to identify freezing of gait in Parkinson's disease. A mobile app developed for usability and effectiveness, showed high reliability in lab tests compared to clinical observations.

The classification of liver and waterborne diseases involves unique difficulties due to the wide inconsistency in clinical presentations, environmental factors, and disease progression rates. For instance, liver diseases often require interpreting complex imaging data, such as ultrasound scans, while waterborne diseases, like cholera and dengue, depend on ecological and geographical variables. Another challenge is the integration of diverse data sources, including environmental, clinical, and patient-reported metrics, into a cohesive diagnostic framework. Limited availability of labeled data and inherent uncertainties in early-stage detection further complicate these tasks. Fuzzy approaches help to manage imprecision, model complex relationships, and provide actionable insights even with incomplete or noisy data. For liver disease, fuzzy inference systems help extract meaningful features from imaging data, offering precise classifications of conditions such as fibrosis and hepatitis. In waterborne diseases, fuzzy models enable public health authorities to predict outbreaks by integrating ecological and epidemiological data for proactive intervention strategies. The ultimate goal is to enhance diagnostic accuracy, reduce costs, and improve resource allocation for better patient and public health outcomes.

4.8 Fuzzy techniques used in classification of lung spinal diseases

To evaluate lung quality, the authors of [129] proposed a cross-sectional investigation based on the information of 41 non-smoking patients. With the correlation between functional records and high-resolution CT scores through FL, a classification for idiopathic pulmonary fibrosis (IPF) was conducted which is based on forced vital capacity (FVC). Aspiratory Function Tests (PFTs) for pneumonic infection are significant in the clinical assessment of patients experiencing "shortness of breath". Hence, the authors of [130], built up a fuzzy approach for a quick understanding of PFT yields. This methodology was compared with past investigations where the proposed approach showed better precision from recently utilized strategies. The authors of [131] proposed a neuro-fuzzy model that consolidated an ANN and an FLS to determine the stage of Huntington's disease (HD). The neural network accomplished the R estimation of 0.98 and mean squared error (MSE) estimations of 0.08, while the FLS gave the last assessment of the subject's response to the condition of illness. The authors of [142] proposed an FNN for spleen segmentation and developed the HYBRIKON image analysis software. Combining region-growing techniques, self-organizing NNs, and fuzzy rules, the system achieved 99% accuracy. The authors of [147] proposed a MAMDANI Inference system for pneumonia and asthma with improved ROC curve. The authors of [214] proposed a hybrid method combining modular ANNs and FL to diagnose pulmonary diseases from digital chest X-rays. Utilizing features like grayscale histograms and texture descriptors, the approach employed a GA for feature reduction, leading to an optimized neuro-fuzzy classifier with notable accuracy on large datasets. Lung and spinal diseases involve significant challenges due to the variation in symptoms, imaging features, and disease progression. For lung diseases, factors like overlapping clinical manifestations (e.g., pneumonia and asthma) and noisy data from PFTs complicate accurate diagnoses. Similarly, spinal diseases often involve complex imaging data, such as MRIs, that require precise segmentation and analysis to identify deviations. FL-based models enhance interpretability and reliability, providing actionable insights for diagnosing and classifying diseases. Techniques like hybrid neuro-fuzzy systems and MISs enable robust decision-making in complex cases, where traditional methods fail.

4.9 Fuzzy techniques used in classification of immunity related diseases, mental illness and typhoid.

The authors of [117] proposed an interval-value fuzzy logic for immune repertoire to perceive both self and non-self-antigens. The type and magnitude of the immune response is dependent on the affinity between the antigen and the T-cell receptor, along with cellular thresholds. The authors of [119] introduced FL-based screening and prediction tool for adult psychoses. This method provided a cost-effective and accurate approach for screening seven adult psychoses and identifying the most dominant one using FL-based expert systems. The authors of [152] proposed a novel technique with the assistance of a fuzzy and FPGA framework to predict the possibility of numerous sicknesses in a provincial territory.

Table 5: Summarizing the related research for fuzzy approaches in classification of diseases of the liver, water borne diseases, lung spinal diseases, immunity related diseases, mental illness and typhoid.

Fuzzy Approaches	Medical Diagnosis/Medical Application	References
Spatial FIS, FIS	Early warning for cholera outbreaks, mass vaccination for treating measles	[108], [109]
Fuzzy AHP approach	Diagnosis of malaria patients	[115]
Fuzzy inference-based approaches	Classification of pancreatic carcinoma and benign pancreatic diseases, determining environmental factors for dengue, Solving biogeographical interaction, Fluid balance control in kidney transplants, Screening and prediction of adult psychoses	[122], [145], [158], [119]
Intuitionistic fuzzy logic (IFL)	Cost prediction of hepatitis treatment	[150]
Fuzzy information-based expert system	Identification of liver fibrosis stage	[153]
Fuzzy logic	Classification of IPF and Diffuse liver diseases, Interpretation of PFT results, freezing of gait identification in PD	[129], [107], [130], [177]
Hybrid (neuro-fuzzy) model	Determining the stage of Huntington's disease, Diagnosing pulmonary diseases from digitized chest X-rays, Spleen segmentation	[131], [214], [142]
MAMDANI Inference system	Pneumonia and asthma approach	[147]
Infinite-value fuzzy inference	Safe collection perception for self and non-self-antigens	[117]
Fuzzy and FPGA system	Prediction of multiple diseases in a rural area	[152]
WBDSS driven by Fuzzy Logic	Diagnosis of thyroiditis (TF)	[190]
GENFIS model	Diagnosing Malaria and Typhoid Fever	[215]

The authors of [190] proposed a Web-Based Decision Support System (WBDSS) using FL, comprising a Knowledge Base (KB) and an FIS. The Root Sum Square (RSS) method drives the inference engine, while the Fuzzifier uses a triangular MF to evaluate decision variables. The Defuzzifier applies the Centroid of Area (CoA) method to produce precise outputs. The authors of [215] proposed the GENFIS model, which combines a Genetic Algorithm with a Neuro-Fuzzy Inference System, tailored to diagnose Malaria and Typhoid fever. By optimizing network parameters using the GA, the system achieved an impressive 97.2% accuracy in the MATLAB testing environment, outperforming existing models.

Screening of diseases, especially those with overlapping symptoms or complex causal relationships (e.g., adult psychoses, malaria, typhoid), pose significant challenges. These challenges naturally include variability in symptom presentation across patients, incomplete or imprecise data from diagnostic tools, and the need to integrate multiple data types, such as clinical measurements, imaging results, and patient histories. Systems such as fuzzy rule-based models, neuro-fuzzy frameworks, and hybrid models like GENFIS utilize the strengths of FL to provide interpretable diagnostic insights. By optimizing system parameters with GA and adding expert knowledge, these techniques improve diagnostic accuracy, reduce costs, and enable the deployment of low-cost, scalable solutions. Ultimately, these advancements aim at enhancing patient care, support medical decision-making, and address global health disparities. Table 5 summarizes the discussions in the above three sections (4.7-4.9).

4.10 Fuzzy techniques used in general medical diagnosis system.

Chen [22] proposed a framework utilizing a weighted fuzzy reasoning calculation for dealing with medical diagnostic issues and used the FS hypothesis and rules for knowledge representation. This permitted every symptom having a different degree of belongingness in the medical diagnosis. The authors of [23] utilized the FSs hypothesis to deal with vagueness and uncertainty when doctors arrive at a conclusion. The authors of [27] developed gene expression profiles comparing patients to healthy individuals and proposed the fuzzy membership test (FM-test) based on FST to identify disease-related genes from microarray data. Results on clinical datasets proved accurate, addressing challenges in medical data processing, such as multiclass and overlapping conditions, where patients may suffer from multiple diseases simultaneously. On the same problem, the authors of [32] built up a fuzzy pattern recognition model with enhanced results. The authors of [33] studied a fuzzy relation-based technique (FR) and naive Bayes (NB) on clinical datasets, which is valuable for classification problems in the clinical area and concluded that FR is insignificantly superior to NB. Key algorithms used in diagnosis include ANNs, Support Vector Machines, Decision Trees, FIS, and their hybrids. The authors of [218] introduced a nonlinear strict distance measure tailored for IFSs, specifically crafted to overcome previous methodological shortcomings, and adeptly differentiate IFSs exhibiting significant hesitancy. This approach finds practical application in diverse areas such as pattern classification, determining the most suitable antivirus face masks for COVID-19, and medical diagnostic processes. The authors of [220] introduced the concept of n-fuzzy sets, an expansion of FSs, to handle greater uncertainties in data as compared to intuitionistic, Pythagorean, and Fermatean FSs. This technique is then applied to enhance Sanchez's approach for medical diagnosis, offering more precise diagnostic capabilities. The authors of [221] studied the concept of bipolar complex fuzzy soft sets and utilized it to develop various trigonometric similarity measures, including both generalized and weighted versions, for analysing complex information. These measures were then applied to real-world scenarios like pattern recognition and medical diagnosis, demonstrating their superiority over existing similarity measures. The authors of [222] proposed an improved correlation coefficient for probabilistic hesitant FSs (PHFSs) developed by integrating a probabilistic adjustment factor, enhancing the measure's effectiveness. This advanced fuzzy technique is then applied to fields such as decision making, medical diagnosis, and cluster analysis, showcasing its practical utility and applicability.

The authors of [143] investigated the uses of an uncommon type of the Type-2 Fuzzy Inference System, which is the Shadowed T2 FIS, and the explanation behind utilizing this methodology (and not another) was on the grounds that gave a good approximation to General T2 FIS, ~~however~~ with additional computational cost ~~decrease~~. A total of 11 benchmark datasets were used to compute the accuracy of the model. The outcomes showed the benefits of utilizing this methodology over ordinary General Type-2 Fuzzy Inference Systems, in so far as it proved better execution in most of the cases and with less computational costs. Fuzzy probability was proposed by the authors of [163] as the fundamental system for taking care of the uncertainties in medical diagnosis and especially aphasia diagnosis. To proficiently build this fuzzy probabilistic model, experimentations were performed that constructed input MFs as well as determined an effective set of input features. In like manner, the authors of [167] proposed some uses of fuzzy logic in clinical determination and specifically used fuzzy logic to identify subjects with diabetes mellitus, renal failure and liver infection. The examination among traditional and fuzzy logic discoveries appears to demonstrate that fuzzy logic is progressively more satisfactory when considered the advancement of biological events. Actually, fuzzy logic is helpful when we have a large snippet of data and when we arrange to scalar amounts. Taking everything into account, as time passes, the advancement of innovation offers new instruments to measure pathological parameters through scalar quantities. So, also it is easy to imagine that later on fuzzy logic will be utilized more in clinical findings. The authors of [178] investigated various fuzzy logic frameworks and grouped fuzzy logic applications in the field of diabetes, iris, heart, breast cancer, dental, cholera, brain tumor, liver, asthma, viral, parkinsons, lung, kidney, huntington and chest illnesses. This examination highlights the advantages of fuzzy logic to the general public and its ability to handle illnesses that, despite everything, need suitable tools for their exact assessment.

The goal of Mansourvar et al. in [180] was to build another completely automated and precise methodology dependent on a fuzzy inference system for the appraisal of the skeletal age in a living person. FL ~~as a smart figuring procedure~~ was introduced to manage uncertainty as well as inadequate information. The framework endeavored to measure eight features that are associated profoundly with development and development of skeletal age. The framework was assessed with standard instances of hand radiographs for subjects somewhere in the range of 11 and 17 years of age. It was indisputably concluded that there was a high linear relation between framework age assessment and chronological age, and the new technique gave reliable outcomes in the estimation of skeletal age. The authors of [181] presented the ASIC structure of a FL circuit for clinical analytic applications. The chip framework utilizes fuzzifier, memory and defuzzifier for storing, and defuzzifying patient information. The proposed circuit utilized ~~triangular~~ trapezoidal MF for fuzzification of patients' information. The authors of [184] cautiously refined and formalized the philosophy for a diagnostic system that incorporates six phases, where the initial three phases work with crisp guidelines, while the last three are utilized on fuzzy models. The authors of [187] proposed OMFAM which eliminates the local optimal problem and applies simulated annealing to advance fuzzy set boundaries related with modified fuzzy ant-miner (MFAM). MFAM utilizes characteristics and prepares case weighting. OMFAM was tested on six clinical cases for creating efficient clinical diagnosis systems. The performance analysis considered both the accuracy and interpretability of the mined rules. Further, it was compared with MFAM, fuzzy ant-miner (FAM), and other classification methods, where it showed superiority over the others.

The authors of [192] developed the Disease Diagnosis Support System (DDSS), which used patient symptoms to identify diseases. It included steps like verifying rules, processing with ANNs, collaborating in the diagnosis process, and determining diagnoses using para-clinical guidelines. The authors of [193] presented a systematic review on Adaptive Neuro-Fuzzy Inference System (ANFIS) and fuzzy cognitive maps for disease classification, and evaluated using accuracy, sensitivity, specificity, and ROC curve analysis. The study also addressed diverse needs across industries, professionals, and researchers, encouraging further exploration of overlooked areas and concluding with recommendations for future research on infectious diseases. The authors of [194] utilized fuzzy approaches for different degrees of hypertension and diabetes. They introduced a logic, which could be consolidated as a pocket gadget in future that would produce an alert at whatever point there was a variation in glucose or pulse levels. The idea of fuzzy inference rules and first-order logic was executed to study this investigation. The authors of [70] developed an interactive approach for multi-criteria group decision-making using IT2 FSs. A relative investigation with different methodologies was performed to approve the adequacy of the proposed technique. Advanced clinical diagnoses require managing vast amounts of heterogeneous and uncertain data, ranging from imaging to patient-reported symptoms and biochemical markers. Challenges include integrating diverse data sources into coherent models, dealing with overlapping symptoms in diseases like diabetes, hypertension, and infections, and ensuring interpretability of diagnostic results for medical professionals. Also, there is a growing demand for portable, cost-effective diagnostic devices that can operate in resource-constrained settings, increasing the complexity of developing reliable systems. Techniques like fuzzy rule-based systems, neuro-fuzzy models, and hybrid approaches enable robust integration of diverse datasets for more accurate and interpretable diagnostics. Fuzzy systems also offer the adaptability needed to customize diagnostic tools for specific diseases, while supporting scalable solutions for portable devices. By enhancing predictive accuracy, reducing diagnostic costs, and improving decision support for healthcare professionals, fuzzy techniques are instrumental in addressing unmet needs in clinical diagnostics.

The authors of [89] proposed an improved MDR method with the fuzzy sigmoid strategy (FSMDR) to distinguish epistasis, which showed better detection rates than other MDR-based approaches. To address the need for diagnoses of stroke, which involves factors like age, sex, blood pressure, diabetes, obesity, heart disease, and smoking, the authors of [90] proposed fuzzy cognitive mapping to assess ischemic stroke risk. Additionally, the Intuitionistic Fuzzy Jensen-Tsalli Divergence measure [91] was introduced under the IFS theory to handle uncertainty and differences in traditional IFSs. Its flexibility and applicability were demonstrated in pattern recognition and medical diagnosis. Davvaz & Sadrabadi [92] confirmed one of the utilizations of IFSs in clinical determination. As a matter of fact, by utilizing the connections between intuitionistic fuzzy sets and symptoms of the patient, they could decide the nature of the disease. The authors of [93] reviewed various soft computing approaches used in healthcare over the past decades, which were classified into five types: clustering model-based systems, expert systems, fuzzy and neuro-fuzzy systems, rule-based systems, and case-based systems. The study focused on the accuracy of these methods, including, methodology, diseases addressed, and accuracy rates.

Table 6: Summarizing the related research for fuzzy approaches in the general medical diagnosis system.

Fuzzy Approaches	Medical Diagnosis/Medical Applications	References
Weighted Fuzzy Reasoning	Medical Diagnostic Issues	[22]
Fuzzy Sets, Shadowed T2 FIS	Medical Diagnosis	[23], [143]
FM-test, Fuzzy Pattern Recognition Model, FR vs. Naive Bayes (NB)	Disease-related gene identification, Multiclass & Non-fresh Membership, Classification issues in the clinical domain	[27], [32], [33]
Nonlinear Strict Distance Measure, N-Fuzzy Sets, Bipolar Complex Fuzzy Soft Sets, Improved Correlation Coefficient for PHFSs	~~IFSs,~~ Sanchez's Approach for Medical Diagnosis, Trigonometric Similarity Measures	[218], [220], [221], [222]
Fuzzy Probability, Fuzzy Logic	Clinical Diagnosis, Aphasia, Diabetes Mellitus, Renal Failure, Liver Disease	[163], [167]
Fuzzy Inference System, ASIC Design of Digital Fuzzy Logic Circuit	Skeletal Age Assessment, Clinical Diagnostic Applications	[180], [181]
Diagnostic System, OMFAM Algorithm	Fresh Rules, Fuzzy Models, Clinical Diagnosis	[184], [187]
DDSS, ANFIS and Fuzzy Cognitive Map, Fuzzy Approaches	Disease Diagnosis, Disease Classification, Hypertension and Diabetes	[192], [193], [194]
Intelligent Model, FSMDR, Fuzzy Cognitive Mapping, Intuitionistic Fuzzy Jensen-Tsalli Divergence, IFSs	Epistasis Detection, Ischemic Stroke Risk, Clinical Diagnosis, Healthcare	[70], [89], [90], [91], [92], [93]
Rule-based Fuzzy Classifiers, Incremental Additive Model for FSs, Two-Layered Fuzzy Rule-Based System and Neural Network, Naive Bayes Estimate	Disease Diagnosis, Aphasia Diagnosis, Health Condition Correction, Acupuncture Methods	[96], [103], [113], [127]

The authors of [96] proposed a technique for developing rule-based fuzzy classifiers, targeted to the performance and interpretability needs of specific applications in the clinical field. They used the NB approximation which optimizes parameters once and independently for each variable, and also made it computationally efficient. A lightweight fuzzy method for differentiating between two similar diseases was proposed by authors of [103]. This approach employed an incremental simple additive model for FSs to support specific diagnoses to generate a support index for a disease. It incorporated fuzzy symptom information, including intensity and duration to demonstrate effectiveness in assisting differential diagnoses. The authors of [113] proposed a two-layer fuzzy rule-based system and a backpropagation feed-forward NN for diagnosing four types of Aphasia such as Anomic, Broca, Global, and Wernicke. Further, mathematical techniques and algorithms for selecting biologically active points (BAPs) and also for improving health through acupuncture were explored in [127]. The results indicated that combining fuzzy decision rules with exploratory analysis provided the highest quality of decision-making by examining various data features. Table 6 summarizes the discussion in this section.

4.11 Fuzzy techniques used in detection of Arthritis and its types

The authors of [148] introduced an active wrist orthosis equipped with a fuzzy logic controller to monitor an individual's health. This device also prevents strain injuries, with its actuator system providing essential motion support to the wrist. A key challenge in arthritis detection is the variability in symptom which makes it difficult to establish precise diagnostic criteria. Naturally, approaches like fuzzy logic controllers excel in handling such variability to provide adaptable and interpretable models for diagnosis. Musculoskeletal disorders (MSDs) are one of the major causes of disability in humans, and their accurate and timely diagnosis is challenging. In this respect, the authors of [149] utilized fuzzy logic to structure clinical decision support systems (CDSSs) that could assist specialists with diagnosing the illness precisely. The challenge in addressing MSDs and related issues lies in the imprecise nature of symptoms in patient-reported data. Fuzzy-based systems enable dynamic and adaptive modeling of this uncertainty to offer personalized diagnostic and therapeutic recommendations. The authors of [156] built an FLS for elbow and wrist recovery in patients. The clinical tests were performed on 18 patients which gave a precision superior to other ML strategies. The authors of [157] proposed a rule-based fuzzy logic system to decide Fibromyalgia syndrome (FMS), a chronic disease in muscles and skeleton. The technique contained rule-based and individual experience of experts, resulting in an accuracy of 95.56%. The authors of [216] addressed the challenge of feature selection in diagnosing knee osteoarthritis patients. Using a fuzzy-based approach, the research not only refined the dimensionality of the problem but also exhibited a marked improvement in performance. This technique successfully achieved an average accuracy of 78.14% with 31 selected features, surpassing other conventional methods and identifying pivotal features.

4.12 Fuzzy techniques used in detecting stomach related diseases and malnutrition

The authors of [154] developed an expert system for hernia diagnosis which showed an accuracy of 72%, also identifying healthy people. The fundamental idea behind the framework was that a health status is reflected by body type. Thus, the features of the nutritional status, based on body type, were determined and compared with reference ranges obtained from healthy subjects. The distinctions were assessed by a fuzzy logic system or a decision tree so as to distinguish malnourished patients [106]. The novel framework provides identification of malnourished patients, and it tends to be applied for the screening and checking of the nutritional status of medical clinic patients. The authors of [140] proposed a technique to study the stability of equilibrium points for systems where direction field is partially known and defined by fuzzy rules. The results provide valuable information which can help in the analysis of traditional models. This system can be applied to more intricate epidemiological models.

4.13 Fuzzy techniques used in detecting problems in spinal cord and wrist problems

The authors of [148] designed an FL-based control system for an active wrist orthosis that is portable, powerful, and lightweight. This system aims to prevent and treat repetitive strain injuries in individuals with high-risk professions involving excessive wrist movement, such as lateral and medial epicondylitis. The authors of [25] applied FST and FL to transform diagnostic rules into a tool providing diagnoses at varying confidence levels. This included definitive, potential, and super-definitive diagnoses. Two fuzzy models and a reference model offering only definitive results were tested on 292 clinical cases from a rheumatic disease hospital, demonstrating effectiveness in enhancing diagnostic accuracy. The authors of [26] proposed a framework for the determination of arthritis utilizing FLC to manage uncertainty and imprecision, so that the information on a specialist can be displayed utilizing an FLC. The exhibition of an FLC relies upon its knowledge base It is seen that the performance of an FLC principally relies upon its rule base, and fine tuning involves optimizing the MFs. The authors of [217] employed a novel segmentation technique combining a probabilistic boosting tree with a fuzzy support vector machine (PBT-FSVM) for spine canal segmentation on MRI datasets. This approach integrated automatic spine canal segmentation using MR data with a fuzzy support vector machine for enhanced accuracy in a fully automated stream pipeline.

4.14 Fuzzy techniques used to detect asthma and pneumonia

The authors of [147] developed a computational model utilizing fuzzy logic dependent on MIS. For the fuzzification of the particulate issue, ozone, sulphur dioxide and temperature, authors considered two relevancy functions for every factor with the linguistic approach. For the yield, a variable number of hospitalizations for asthma and pneumonia, the authors considered five importance functions. The precision of the model was assessed by the ROC. Fuzzy logic provided accurate results for pollutant exposure and duration of hospitalization for pneumonia and asthma approach. Table 7 summarizes the discussions about fuzzy approaches in the detection of arthritis and its types, stomach related diseases and malnutrition, asthma and pneumonia, and to detect problems in the spinal cord and wrist.

Table 7: Summarizing the related research for fuzzy approaches in detection of arthritis & its types, stomach related diseases & malnutrition, asthma & pneumonia, and detecting problems in the spinal cord and wrist

Fuzzy Approaches	Medical Diagnosis/Medical Applications	References
Fuzzy Logic Controller, FST	Diagnostic tool for musculoskeletal disorders at different confidence levels., diagnosis of Arthritis, monitoring health using a wrist orthosis, preventing strain injuries, providing motion support to the wrist.	[25], [26], [148]
Fuzzy logic	Designing CDSSs for accurate diagnosis of MSDs	[149]
FLS	Elbow and wrist recovery in patients	[156]
Rule-based fuzzy logic technique	Determining (FMS)	[157]
Fuzzy-based approach for FS	Diagnosing knee osteoarthritis patients	[216]
Fuzzy logic system	Hernia diagnosis, identifying healthy individuals.	[154]
FST	Directly transmitted diseases	[140]
Probabilistic boosting tree, FSVM	Spine canal segmentation on MRI datasets	[217]
Fuzzy logic (Mamdani's method)	Computational model for hospitalizations due to asthma and pneumonia based on pollutant exposure.	[147]

4.15 Fuzzy techniques used in fibroses diagnosis and dementia diagnosis

Liver cirrhosis, the advanced stage of chronic liver disease, is a major risk factor for liver cancer and can lead to sudden death. The authors of [153] proposed the Fuzzy Fibrosis Decision Support (F2DS) system for predicting liver fibrosis stages. The system demonstrated high accuracy in diagnosing the stages of fibrosis and could be integrated into healthcare systems to assist doctors in their daily practice. The authors of [116] explored the development of an ambient intelligent system for monitoring dementia patients at home. This system deployed groups of subtle wireless sensors in specific locations within a patient’s home, accessible through standardized interfaces on an open middleware platform. Intelligent agents associated with each sensor group learnt fuzzy rules to model the patient's real-time behaviour in their environment.

4.16 Fuzzy techniques used in infant care and gene to gene interaction (GGI)

Infant screening plans are a daily schedule for infant care, thus, authors of [182] presented a fuzzy inference system to help infant screening, which covered 46 metabolic disorders using up to 42 diagnostic inputs. The system achieved 98.7% diagnostic accuracy when tested with two sample types from three sources, while significantly reducing processing time compared to laboratory tests. The authors of [80] introduced an Empirical Fuzzy MDR (EF-MDR) method to identify GGI, based on the maximum likelihood of the proportion of cases (or controls) as the membership degree of genotype combinations. The method provided a direct approach for estimating membership degrees, calculated using a maximum likelihood estimator for each genotype combination.

4.17 Fuzzy logic techniques used to detect Crohn's disease and risk assessment of myocardial infarction.

The authors of [169] proposed an FL-based model for selecting off-label anti-TNF treatments for Crohn's disease (CD), including Infliximab (10 mg/kg/2 months), Adalimumab (80 mg/14 days), and Certolizumab (200 mg/2 weeks). Unlike traditional logic, FL variables have degrees of truth, making it widely applicable across fields like financial analysis and AI. The authors of [199] proposed an automated method for designing a CDSS for CAD diagnosis. The model integrates Random Forest ~~computation~~, C5.0 decision tree algorithms, and fuzzy modelling in two stages: first, Random Forest ranks features, and C5.0 generates crisp rules; second, FISs are built by automatically generating fuzzy-weighted rules from the crisp ones. Experimental results showed a classification accuracy of 90.50% with reduced training time, using UCI heart disease datasets, outperforming previous methods.

4.18 Fuzzy techniques used to monitor ICU patients and monitor urinary infections and improve X-ray quality

Leite et al. [188] presented a fuzzy model for helping clinical analysis of Intensive Care Unit (ICU) patients and their vital signs observed through a multi-parameter heart screen. Intelligent frameworks strategies were utilized in the data procurement and preparing it into useful data. Additionally, the authors also performed pre-diagnosis to immediately update the clinical staff in cases of emergency. The challenge here lies in managing continuous streams of data from multiple sources while prioritizing critical alerts for clinical staff. Fuzzy systems address this by integrating real-time data and providing interpretable decision support. The authors of [189] proposed a novel approach for uncomplicated urinary tract infection (uUTI) treatment, and introduced an adaptable methodology of fuzzy cognitive Maps (FCMs) to deal with uncertainty and missing data. A product device is introduced to deliver a DSS module for uUTI treatment. The software was assessed in 38 patient cases, indicating its usefulness and exhibiting that the utilization of the FCMs as powerful models is evident and acceptable.

Table 8: Summarizing the related research for fuzzy approaches in in medical diagnosis application for Section 4.15-4.18

Fuzzy Approaches	Medical Diagnosis/Medical Application	Refs.
F2DS	Fuzzy information-based master system for liver fibrosis stage prediction.	[153]
Fuzzy rules	Monitoring dementia patients using ambient smart system sensor devices.	[116]
Fuzzy inference system	Infant screening, detecting 46 metabolic errors with high accuracy and speed.	[182]
Fuzzy MDR	Identifying GGI using Fuzzy MDR for genotype combination assessment.	[80]
Fuzzy logic-based model selection	Model selection for off-label use of antiTNF in Crohn's disease.	[169]
Fuzzy modeling for CAD assessment	Automatic CDSS for CAD assessment using RF, C5.0 decision tree, and FSs	[199]
Fuzzy model for ICU patient diagnosis	Clinical diagnosis of ICU patients based on multi-parameter heart monitor data.	[188]
Fuzzy Cognitive Maps (FCMs)	Clinical decision support in uUTI treatment.	[189]
FGRM	Fuzzy gamma reasoning model for low-contrast X-ray image enhancement	[195]

Mouzai et al. [195] proposed methodology for low-contrast X-ray image improvement, dependent on brightness adjustment and utilizing a fuzzy gamma rule model (FGRM). To accomplish this, three stages were followed such as pre-processing, fuzzy modelling for versatile gamma correction (GC), and quality appraisal. The experimentation with the proposed FGRM approach on three databases (cervical, lumbar, and hand radiographs) yielded great outcomes in terms of contrast modification and good quality images. Table 8 summarizes the discussions in the above four section (4.15 -4.18).

5 DISCUSSION AND CONCLUDING REMARKS

This paper presents a detailed study and overview of the research undertaken in the field of medical diagnosis from the perspective of fuzzy sets-based approaches. To do so, first we discovered the structures and development using a precise bibliometric analysis, which revealed the growing number of publications in this area over the years. We also summarized the fuzzy sets-based approaches such as T1 FSs, T2 FSs, IT2 FSs, CWW, Per-C, and FIS which are most often used to address the wide range of uncertainties related to medical diagnosis. Further, while exploring the citation topic and analyzing keywords from publications, we identified several application areas where FSs based approaches have been used such as ECG, image segmentation, lung cancer, mammograpgy, rheumatology, pattern recognition, etc. Finally, we have extensively studied and discussed the publications in FSs-based approaches for medical diagnosis and classified several areas where fuzzy techniques have been used for diagnosis such as in detecting diabetes, cancer, medicine classification, bio informatics, HIV AIDS, Anesthetics, amino acids, leukocytes in blood, heart diseases, brain diseases, liver and water borne diseases, Lung spinal diseases, mental illnesses and typhoid, general medical diagnosis systems, arthritis, stomach diseases & malnutrition, spinal cord and wrist problems, asthma and pneumonia, fibroses and dementia diagnosis, infant care and gene to gene interaction, Crohn's disease and in risk assessment of myocardial infarction, to monitor ICU patients and urinary infections and the quality to improve X-rays.

While extensively exploring the related literature, we found that the most common data sources utilized in medical diagnosis, where fuzzy sets-based approaches have found their applications. These data sources include medical information such as patient symptoms, test results, patient history, verbal statements, etc. These sources characterized by inherent uncertainty, are modelled with the help of various fuzzy sets-based tools (T1 FSs, T2 FSs, etc,) while including inputs from human experts who are medical practitioners and professionals in this case. The outcome of the resulting formulation is processed using fuzzy inference engines, defuzzification, linguistic summarizations, etc, for decision making and medical diagnosis. Fig. 13 pictorially represents the overall process of how fuzzy sets-based approaches are employed in the field of medical diagnosis.

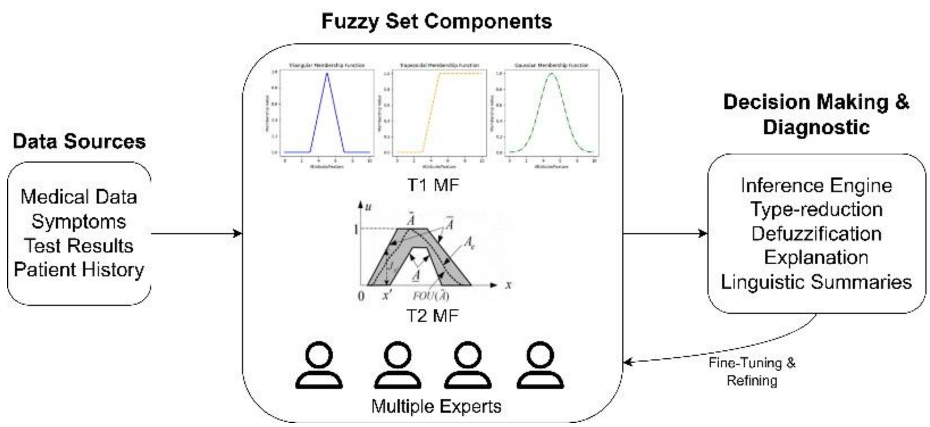

Fig. 13: Fuzzy sets based medical diagnosis ecosystem

The discussion in the reviewed articles validates the versatility and effectiveness of the application of FSs-based approaches in medical diagnosis across diverse domains. The concluding remarks are summarized as follows:

- Wearable sensors, when coupled with T2 FIS, demonstrated promise in real-time patient monitoring, aiding personalized recommendations in diabetes management. T2 FSs have also shown their capability in enhancing the clarity of amino acid patterns, surpassing T1 FSs.
- Fuzzy logic integration in applications such as early detection of diabetes and breast cancer resulted in improved accuracy.
- Fuzzy inference engines have shown accuracy levels ranging from 84.4% to 99.9% in medical fields including HIV routine development, cardiovascular health, and fluid infusion decisions. Traditional FSs for fluid infusion rate decisions, clinical diagnosis, and brain cooling procedures, showed an accuracy range from 87.0% to 99.9%
- Authors have even achieved an accuracy of 100% in in real-time validation for disease diagnoses utilizing FL. Its versatility has also been observed in skeletal age assessment to infectious disease research. FLS designed for diagnosing FMS achieved 95.56% accuracy in finding chronic muscle and skeletal conditions.
- Several publications have demonstrated the enhanced accuracy of fuzzy systems where they have achieved accuracy up to 98%, 92.85%, and 88.1 % in cardiovascular health exhibits promising diagnostic accuracy, heart disease models, and Alzheimer's disease diagnosis, respectively.
- Fuzzy inference system has provided additional support to the decision support system for clinicians where fuzzy expert systems for disease classification enabled enhanced sensitivity, specificity, and accuracy of 99.67%, 99.56%, and 98.75%, respectively.
- Various hybrid models are also being developed for additional improvement such as HFMC synergizing Modlem2 and fuzzy classifiers for liver disease diagnosis which achieved classification accuracy of 99.14%. FSs integrated with statistical feature extraction successfully addressed the challenges in breast cancer detection where GENFIS model attained 97.2% accuracy for diagnosing malaria and typhoid fever.

Despite the achievements in various domains of medical diagnosis, the challenges including computational complexity from higher order fuzzy sets and explainability of the model remain and ongoing research need to further refine the fuzzy sets-based applications.

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