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Fuzzy decision support systems to diagnose musculoskeletal disorders: A systematic literature review

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ABSTRACT

Background and objective: Musculoskeletal disorders (MSDs) are one of the most important causes of disability with a high prevalence. The accurate and timely diagnosis of these disorders is often difficult. Clinical decision support systems (CDSSs) can help physicians to diagnose diseases quickly and accurately. Given the ambiguous nature of MSDs, fuzzy logic can be helpful in designing the CDSSs knowledge bases. The present study aimed to review the studies on fuzzy CDSSs to diagnose MSDs.
Methods: A comprehensive search was conducted in Medline, Scopus, Cochrane Library, and ISI Web of Science databases to identify relevant studies published until March 15, 2016. Studies were included in which CDSSs were developed using fuzzy logic to diagnose MSDs, and tested their accuracy using real data from patients.
Results: Of the 3188 papers examined, 23 papers included according to the inclusion criteria. The results showed that among all the designed CDSSs only one (CADIAG-2) was implemented in the clinical environment. In about half of the included studies (52%), CDSSs were designed to diagnose inflammatory/infectious disorder of the bone and joint. In most of the included studies (70%), the knowledge was extracted using a combination of three methods (acquiring from experts, analyzing the data, and reviewing the literature). The median accuracy of fuzzy rule-based CDSSs was 91% and it was 90% for other fuzzy models. The most frequently used membership functions were triangular and trapezoidal functions, and the most used method for inference was the Mamdani.
Conclusions: In general, fuzzy CDSSs have a high accuracy to diagnose MSDs. Despite the high accuracy, these systems have been used to a limited extent in the clinical environments. To design of knowledge base for CDSSs to diagnose MSDs, rule-based methods are used more than other fuzzy methods.

1. Introduction

Musculoskeletal Disorders (MSDs) are one of the most important leading causes of years lived with disability (YLD). The prevalence of these disorders was reported 18.5% (16.4–20.9%) by the global burden of diseases study (2015) [1]. MSDs include a wide range of injuries affecting muscles, joints, ligaments, tendons, peripheral nerves, and supporting blood vessels. These disorders lead to a reduction in work efficiency of individuals and are one of the most common reasons for work absence [2]. Significant prevalence, chronicity, and disability resulting from these disorders impose substantial economic burdens on societies worldwide [3]. Therefore, timely and accurate diagnosis of these disorders and initiating the treatment of them are of great importance.

MSDs are not easy to diagnose on time because the nature of knowledge about them is ambiguous and the level of experts' knowledge varies [4]. Physicians often use the trial and error strategy for the diagnosis and treatment of these disorders [5]. Incorrect diagnosis of these disorders can lead to later expensive investigations and delayed treatment.

Clinical decision support systems (CDSSs) can help physicians with disease diagnosis. These diagnosis CDSSs provide the patient's clinical information and knowledge about the disease at the time and place required by the clinical staff. The studies have shown that these systems are highly accurate in diagnosis of diseases [6–8] and mostly improve the performance of healthcare providers [9].

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Table 1
Keywords and MeSH terms related to fuzzy logic, decision support system, and diagnosis.

Domain	Keywords	MeSH terms
Fuzzy	Fuzzy	–
Decision support system	Decision support system, decision support tool, reminder system, reminding system, alert system, alerting system, computer assisted decision making, computer assisted diagnosis, computer assisted therapy, expert system, CDS, order entry system, computerized order entry, computerized prescriber order entry, computerized provider order entry, computerized physician order entry, electronic order entry, automated order entry, CPOE, electronic prescribing, electronic prescription, computer assisted drug therapy	Clinical decision support systems, computer assisted decision making, computer assisted therapy, expert systems, medical order entry systems
Diagnosis	Diagnose, diagnoses, diagnosis, diagnostic, detection, identification, recognition	Diagnose

The knowledge base is one of the key components of any CDSS. A variety of methods are used to organize and formalize the knowledge in the knowledge base. These methods include neural network, Bayesian network, rule-based reasoning, decision tree, genetic algorithm, and fuzzy logic [10–14]. Given the ambiguous nature and uncertainty of medical knowledge, among these methods the fuzzy logic has a significant ability to deal with uncertainty and ambiguity. Fuzzy logic models human knowledge in the form of linguistic variables [15]. Fuzzy sets allow for the use of traditional symbolic systems in the continuous form, which is important because medicine is a continuous domain [16]. In a systematic review that assessed the accuracy of computer technologies in pain management, the fuzzy logic methods have the highest accuracy in medical diagnosis compared to other knowledge modeling methods [17].

Given the wide range of MSDs and the ambiguous nature of knowledge of these disorders, many studies have used fuzzy logic methods to model knowledge of these disorders to use in the CDSSs knowledge base [18–21]. However, there are questions about the accuracy of these systems, their rate of use in the clinical environment, the type of disorders they have been created to diagnose, the knowledge source of these systems, the membership function, and the inference method that is most used. Therefore, it appears necessary to aggregate the results of studies related to the design and test of Fuzzy CDSSs for the diagnosis of MSDs.

Questions that the present study attempted to answer are as follows: (1) how accurate are fuzzy CDSSs in diagnosis of MSDs? (2) how many of these systems have been used in clinical settings? (3) which type of MSDs have these systems been created for? (4) what are the knowledge sources of these systems? (5) which of the fuzzy logic methods has been used for the modeling of knowledge in these systems?

2. Methods

The present study was reported following Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) proposed by Moher et al. [22].

2.1. Data sources and search strategies

A systematic and comprehensive search was performed in the databases of Medline (through PubMed), Scopus, Cochrane Central Register of Controlled Trials, and ISI Web of Science to identify relevant studies published until March 15, 2016. The search strategy included a combination of keywords and MeSH terms related to fuzzy logic, CDSS, and diagnosis. Due to the large number of keywords related to MSDs, the search strategy did not specify the type of disease, and the choice of studies related to these diseases was carried out by the researchers at the screening stage of the articles. Table 1 shows the complete list of keywords and terms used in the search.

2.2. Eligibility criteria

Studies were included that met all the following criteria: (1) the system was designed to diagnose MSDs; (2) one of the fuzzy logic methods was used for knowledge modeling; (3) the diagnostic accuracy of the system was tested using real patient data and the result was reported. The exclusion criteria were (1) the system was designed for prediction, risk assessment, treatment, or screening of MSDs; (2) the results of the system test was not reported quantitatively; (3) reviews, editorials, and conference proceedings; (4) the operation of the system was based on image processing; (5) the articles whose full text was not available in the English language; and (6) the systems whose knowledge modeling method was not explicitly explained.

2.3. Data extraction

Two reviewer independently screened the titles and abstracts of the identified articles. The full text of the articles was retrieved and reviewed if it was considered potentially relevant at least one reviewer. Any disagreement between the reviewers was resolved by consensus.

The following data were extracted from the included studies and entered into a spreadsheet: authors' name, year of publication, country that the system was designed there, disease, user of system, implementation in clinical environment, source of data for training and testing of system, sample size, time of data gathering (prospective or retrospective), source of knowledge, result of testing, fuzzy method for designing of system, and detailed information about fuzzy method.

Data extraction from the included studies was done by the first reviewer and was independently checked and approved by the second reviewer. In studies where the system user was titled "physician, general practitioner, family doctor, inexperienced medical doctor and non-specialist physician", the term of "clinician" was used as the system user. Retrospective studies are those that the data used to test the system are collected before the creation of the system and prospective studies are those that the data to test the system are collected after the creation of the system.

2.4. Data-synthesis and analyses

Meta-analysis was not performed due to the heterogeneity of methodology used in the included studies and methods of reporting results. The results of the included studies were reported using descriptive statistics. In studies that reported a separate result for each test stage, only the results of the final test stage were reported, and in studies that reported separate results for each of the rules or each stage of the disease, a mean was calculated and reported. MSDs are categorized based on the Textbook of Disorders and Injuries of the Musculoskeletal System: An Introduction to Or-

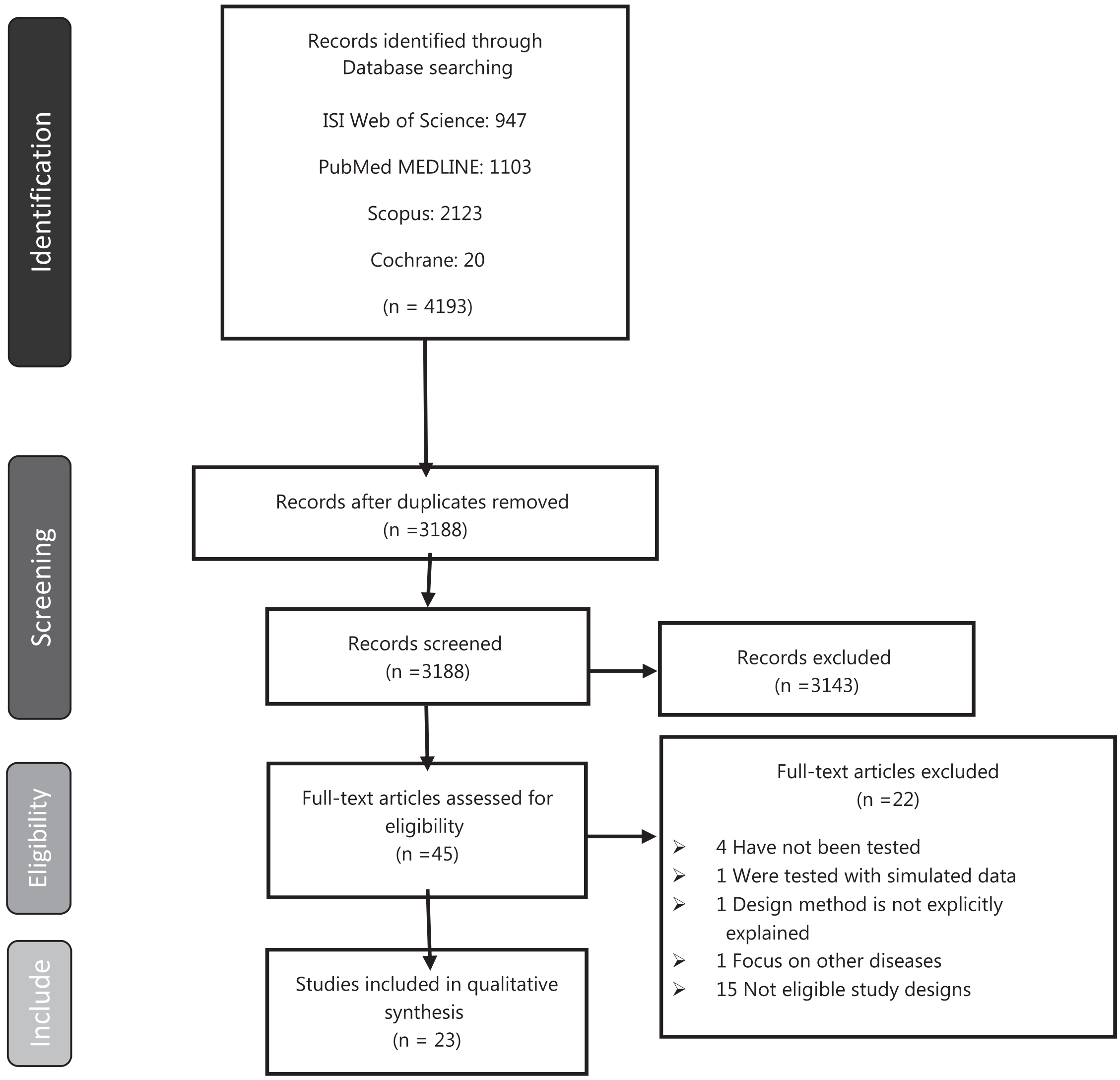

Fig. 1. Flow diagram of the literature search and study selection.

thopedics, Fractures and Joint Injuries, Rheumatology, Metabolic Bone Disease and Rehabilitation [23].

3. Results

3.1. Study selection

As shown in Fig. 1, a total of 4193 records were obtained by searching the Medline, ISI Web of Science, Scopus, and Cochrane databases, of which 3188 remained after removing the duplicates. After reviewing the titles and abstracts and matching with the inclusion and exclusion criteria, 45 papers remained for full-text review. Finally, 23 eligible studies included in this review.

3.2. General characteristics of the included studies

The general characteristics of the included studies are presented in Table 2. The oldest and newest papers were published in 1985 and 2014, respectively. The 23 included papers were from 23 unique studies. Six studies were conducted in Austria [18,24–28], four in India [20,29–31], three in Italy [32–34], three in Turkey [19,35,36], and one study in each of the following countries: Russia [37], Bosnia and Herzegovina [38], Brazil [39], France [40], Greece [41], Slovenia [42] and Spain [21].

To acquire knowledge for systems in the included studies one of the following three methods or a combination of them was used: (1) knowledge acquisition from the medical expert, (2) data analysis, and (3) literature. In 16 studies (70%) a combination of these three methods was used. In the rest of studies (30%) only one of the methods was used (data analysis in four studies [19,33,35,36], experts' knowledge in two studies[38, 39] and literature in one study [25]).

The user of the system was mentioned in 17 studies (74%). Clinicians were system users in 16 studies. Also, two systems could be used as a training tool for medical students [19,42]. In two studies [30,31], the system user was a patient. Only in five studies [18,24,26–28], the system was used to diagnose MSDs in clinical environments, all of which were related to the CADIAG-2 system.

Table 3 shows the MSDs categories that CDSS was designed for their diagnosis. While in about half of the included studies (52%), CDSSs were used to diagnose inflammatory/infectious disorder of the bone and joint, in none of them a system was designed to diagnose congenital/hereditary disorders, idiopathic disorders, and neoplasm of musculoskeletal tissue.

Table 2
General characteristics of the included studies.

Reference (Authors, year, country)	Disease	Source of knowledge	Source of data (train, test)	User	Real implementation	Prospective /retrospective
[19] (KELES, 2014, Turkey)	Vertebral column diseases (disk hernia and spondylolisthesis)	Analyzing the data	UCI dataset	• Clinician • Medical Students	No	Retrospective
[29] (Kunhimangalam et al., 2014, India)	Peripheral neuropathy	• Analyzing the data • Expert	Patient data from hospital	Clinician	No	Retrospective
[20] (Kunhimangalam et al., 2013, India)	Carpal tunnel syndrome	• Analyzing the data • Expert • Literature	Patient data from hospital	• Clinician • Specialist	No	Retrospective
[37] (Al-kasasbeh et al., 2013, Russia)	Backbone osteochondrosis	• Expert • Literature	• students and teachers from University • Patient data from hospital	–	No	Prospective
[38] (Subasi et al., 2012, Bosnia and Herzegovina)	Neuromuscular disorders	Expert	Patient data from hospital	Clinician	No	Prospective
[39] (Picon et al., 2012, Brazil)	Diabetic neuropathy	Expert	Patient data from hospital	Clinician	No	Retrospective
[35] (Sari et al., 2012, Turkey)	Low back pain	Analyzing the data	Patient data from hospital	–	No	Prospective
[30] (Singh et al., 2012, India)	Arthritis	• Analyzing the data • Expert	Patient data from Research Centre	Patient	No	Retrospective
[31] (Blessia et al., 2011, India)	Osteoarthritis	• Analyzing the data • Expert	Patient data from hospital	• Clinician • Patient	No	Retrospective
[41] (Moustakidis et al., 2010, Greece)	Osteoarthritis	• Analyzing the data • Expert • Literature	Patient data	–	No	Retrospective
[36] (Koçer, 2010, Turkey)	Neuromuscular disease	Analyzing the data	Patient data from hospital	–	No	Prospective
[32] (Binaghi et al., 2008, Italy)	Temporomandibular disorders	• Literature • Expert	Patient data from hospital	Clinician	No	Prospective
[42] (Zelic et al.,1997, Slovenia)	Sport injuries	• Analyzing the data • Expert	Patient data from hospital	• Clinician • Medical Students • Specialist	No	Retrospective
[25] (Leitich et al., 1996, Austria)	Rheumatoid arthritis	Literature	Patient data from hospital	–	No	Retrospective
[40] (Duckstein et al., 1995, France)	Peripheral polyneuropathy	• Analyzing the data • Expert	Patient data from hospital	–	No	Prospective
[21] (Belmonte-Serrano et al.,1994, Spain)	Arthritis and collagen diseases	• Expert • Literature	Patient data from hospital	Clinician	No	Retrospective
[33] (Binaghi et al., 1993, Italy)	Postmenopausal osteoporosis	Analyzing the data	Patient data from hospital	Clinician	No	Retrospective
[34] (Binaghi et al., 1990, Italy)	Osteoporosis	• Analyzing the data • Expert	Patient data from hospital	Clinician	No	Retrospective
[18] (Adlassnig et al, 1985, Austria) [24] (Leitich et al., 2001, Austria) [26] (Adlassnig et al., 1993, Austria) [27] (Kolarz et al., 1986, Austria) [28] (Adlassnig et al, 1985, Austria)	Rheumatic diseases	• Analyzing the data • Expert • Literature	Patient data from hospital	Clinician	Yes	Prospective

Table 3
Classification of musculoskeletal disorders.

Classification of musculoskeletal disorders	Reference
Inflammatory/infectious disorders of bones and joints	[18,19,21,24–28,30–32,41]
Neuromuscular disorders	[29,36,38,40]
Degenerative disorders of joints and related tissue	[19,20,32,35]
Metabolic disorders of bone	[33,34,39]
Disorders of epiphyses and epiphyseal growth	[37]
Traumatic disorders	[42]
Congenital/hereditary disorders	–
Idiopathic disorders	–
Neoplasm of musculoskeletal tissue	–

Table 4
Characteristics of fuzzy rule-based systems.

Reference	Details of fuzzy method							Sample size (test)	Results	Reference for diagnosis
	Linguistic variables	Membership function	Fuzzy operator	Fuzzy inference	Number of rules	Defuzzification method	Software			
[19]	Small, Medium, Large	Triangular	AND	–*	8	–	Visual Studio and SQL server	305	Sensitivity: 94% Specificity: 71% PPV**: 87% NPV***: 86%	Patient data
[29]	Very low, Low, Normal, High, Very high	Triangular and trapezoidal	AND	Mamdani	105	Centroid calculation	MATLAB	104	Accuracy: 93.26% Sensitivity: 91.58% Specificity: 98.01% PPV: 94.01% NPV: 96.41%	Clinical diagnosis
[20]	Very low, Low, Normal, High, Very high, Absent, Mild, Moderate	Triangular and trapezoidal	AND	Mamdani	75	Centroid calculation	MATLAB	135	Accuracy: 98.46% Sensitivity: 94.98% Specificity: 97.76% PPV: 94.65% NPV: 96.56%	Clinical diagnosis
[37]	Present, Rare, Frequent, Weak	–	–	–	–	–	–	460	Accuracy: 81% Sensitivity: 79% Specificity: 81%	Clinical diagnosis
[39]	Absent, Present, Low, Moderate, High, Short, Long	Triangular and trapezoidal	AND	Mamdani	96	Centroid calculation	–	50	Accuracy: 91%	Clinical diagnosis
[30]	No pain, Min, Max	Triangular and trapezoidal	AND	–	30	Centroid calculation	MATLAB	150	Accuracy: 100%	Patient data
[31]	No pain, Min, Max	Triangular and trapezoidal	AND	Mamdani	33	Centroid calculation	MATLAB	3	Accuracy: 91%	Clinical diagnosis
[32]	Present, Absent, Low, Medium, High	–	AND-OR	MAX-DOT	–	–	–	50	Accuracy: 100%	Clinical diagnosis
[25]	–	–	–	–	–	–	–	292	Definite level: Sensitivity: 72.6% Specificity: 87.0% Possible level: Sensitivity: 73.3 - 85.6% Specificity: 83.6 - 87.0% Super definite level: Sensitivity: 39.0 - 63.7% Specificity: 90.4 - 95.2%	Clinical diagnosis
[21]	Impossible, Almost impossible, Slightly possible, Moderately possible, Possible, Quite possible, Very possible, Sure	–	AND	–	1058	–	MILORD environment	32	Accuracy: 75%	Clinical diagnosis
[33]	Very increased, Increased, Normal, Decreased, Very decreased, Very low, Low, Medium, High, very High	–	AND-OR	–	–	–	–	150	Accuracy: 92%	Clinical diagnosis
[34]	Very increased, Increased, Normal, Decreased, Very decreased, Very low, Low, Medium, High, very High	Sigmoid	AND-OR	Mamdani	2756	–	Prolog	25	Accuracy: 87%	Clinical diagnosis

(continued on next page)

Table 4 (*continued*)

Reference	Details of fuzzy method							Sample size (test)	Results	Reference for diagnosis
	Linguistic variables	Membership function	Fuzzy operator	Fuzzy inference	Number of rules	Defuzzification method	Software			
[18]	Always almost, Always, Vary often, Often, Medium seldom, Very seldom, Almost never, Never, Very strong, strong, Weak, Very weak	–	Max-Min	–	–	–	–	426	Accuracy: 93.7%	Clinical diagnosis
[24]								54	Among the first five hypotheses: 48%	Clinical diagnosis
[26]								300	Accuracy: 89.3% Sensitivity: 83.3% Specificity: 95.3%	Clinical diagnosis
[27]								322	Accuracy: 81.7%	Clinical diagnosis
[28]								327	Accuracy: 81%	Clinical diagnosis

*Not mentioned; **Positive Predictive Value; ***Negative Predictive Value.

Table 5
Characteristics of fuzzy systems that designed with methods other than rule base.

Reference	Details of fuzzy method						Sample size		Results	Reference for diagnosis
	Fuzzy method	Membership function	Linguistic variables	Fuzzy operator	Fuzzy inference	Software	Train	Test		
[38]	FSVM	–*	–	–	–	–	18	9	Accuracy: 97.67 ± 0.82 Specificity: 95.25% Sensitivity(myopathic): 98.25% Sensitivity(neurogenic): 99.5%	–
[35]	ANFIS	Triangular	–	–	Sugeno	MATLAB	169	169	Accuracy: 97.2%	Patient data
[41]	FDT-SVM**	Sigmoid	Normal, Moderate, Severe	MAX	–	–	32	4	Accuracy: 93.44%	Patient data
[36]	Neuro-fuzzy system	Triangular	Small, Medium, Large	AND	–	–	87	90	Accuracy: 90%	Diagnostic test
[42]	1) Naive Bayes-fuzzy 2) Semi-naive Bayes-fuzzy	–	–	–	–	–	83	35	Accuracy Naïve Bayes-fuzzy: 69.4% Accuracy Semi-naïve Bayes-fuzzy: 59.4%	Patient data
[40]	Distance-based Fuzzy number approach	Triangular, gaussian, bi-gaussian	Normal, Border-line, Clear-cut, Severe	–	–	C language on McIntosh	203	291	Accuracy: 90%	Clinical diagnosis

*Not mentioned; ** Fuzzy decision tree-based support vector machines.

3.3. The fuzzy method used to design the CDSS knowledge base

Tables 4 and 5 show the characteristics of fuzzy systems and methods used to design the knowledge base. In some of the included studies [25,37,38,42], the details of fuzzy methods were not stated. Also, in five studies that were related to CADIAG-2 system the details of fuzzy methods were not mentioned [18,24,26–28]. The design methods of knowledge base were rule-based in 17 studies (74%) (Table 4). In other studies (6, 26%), combined methods such as Adaptive Neuro-Fuzzy Inference System (ANFIS) and Fuzzy Support Vector Machines (FSVM) were used to design the CDSS knowledge base (Table 5).

The membership functions used to determine the degree of membership were: triangular, trapezoidal, Gaussian, bi-Gaussian, and sigmoid. Of the eleven studies that mentioned their membership functions, five used a combination of triangular and trapezoidal [20,29–31,39], three used triangular [19,35,36], two used sigmoid [34,41], and one used a combination of triangular, Gaussian, and bi-Gaussian methods [40].

Table 6
Sample size and accuracy of the systems.

Design methods	Sample size Test	Train	Accuracy
Rule-based	–	Median: 150 Range: 3–460 IQR1 = 50 IQR3 = 314	Median: 91% Range: 48% - 100% IQR1 = 81, IQR3 = 93.7
Other fuzzy methods	Median: 85 Range: 18–203 IQR1 = 28.5, IQR3 = 177.5	Median: 62.5 Range: 4–291 IQR1 = 7.7, IQR3 = 199.5	Median: 90% Range: 59.4% - 97.67% IQR1 = 69.4, IQR3 = 97.2

Seven studies mentioned their inference method, of which five studies used the Mamdani method [20,29,31,34,39], one study used the Sugeno method [35], and one used the MAX-DOT method [32]. Five studies mentioned the defuzzification method, [20,29–31,39], all of which were centroid calculations. Eight studies mentioned the number of rules used to design the CDSSs knowledge base [19–21,29–31,34,39].

3.4. Fuzzy CDSSs accuracy test results for MSDs

The median of the number of samples used to train and test the systems and their results are presented in Table 6. The median of accuracy was 91% for fuzzy rule-based systems and 90% for other fuzzy models. The accuracy of two systems was 100% both of which used the rule-based design method [30,32]. The lowest accuracy was 48%, which used the rule-based design method, too [24]. The sensitivity and specificity of the diagnosis were reported in seven studies. The lowest and highest sensitivity were 72.6% [25] and 99.5% [38], respectively. The lowest and highest specificity were 71% [19] and 98.01% [29], respectively.

4. Discussion

This review aggregated the results of the studies that have used fuzzy logic to design a CDSS to diagnose MSDs and have tested the system's accuracy. The results of this study showed that only one system (CADIAG-2) was used in the clinical environment. In about half of the included studies (52%), CDSSs were used to diagnose inflammatory/infectious disorder of the bone and joint. In most of the included studies (70%), the system knowledge was acquired using a combination of three methods of acquisition from experts, analyzing the data, and literature. The median accuracy of the systems that used rule-based methods was 91% and it was 90% for other fuzzy methods. Triangular and trapezoidal functions were the most used membership functions. Mamdani method was the most used method for inference.

The results of this study showed that among the designed systems, only CADIAG-2 was used in the clinical environment for the diagnosis of MSDs. The implementation and use of just one system among the designed systems despite their high accuracy might be due to the challenges that the implementation of information systems in clinical environments entail. A review study that focuses on the challenges of using expert systems and neural networks in the medical domain has shown that the implementation of these systems faces many challenges [43]. These challenges are related to: system maintenance, inputting patients' data into the system, knowledge acquisition, modeling medical knowledge, the system's validation and evaluation, concerns about system's wrong recommendations, irresponsibility of people related to the system (system developer, knowledge engineer and physician), limited clinical domains of the systems, and the lack of the integration of the systems with the electronic medical records [43]. The CADIAG-2 has used the following solutions to cope with these challenges: connected to a medical information system and solved the problems of manual data entry, incorporated a wide range of clinical domain (267 diseases), and also used a combination of methods to gain knowledge. However, despite these solutions, the need to improve the knowledge of the system, the need to train system users, and the lack of complete data were mentioned as the challenges of implementing CADIAG-2 [26,44,45]. Therefore, it is necessary to consider these challenges before implementing these diagnostic systems in the clinical environment and to find suitable solutions for them.

The results of this study showed that about half of the tested systems (52%) were designed to diagnose inflammatory/infectious disorder of the bone and joint. The rheumatic disease was the most examined disease by the researchers. Of the reasons for the high attention of the researchers to this category of MSDs were the difficulty of diagnosing the disease for nonspecialist physicians, lack of a clear-cut nosology, the need to consider a combination of symptoms, signs and clinical findings for diagnosis, and non-defined specific boundaries of these types of diseases [21,25,30].

The knowledge base is an important part of CDSSs [46], and knowledge acquisition is a bottleneck in creating these systems [47]. The results of this study showed that in most of the included studies (70%), the knowledge was extracted using a combination of methods of acquisition from experts, analyzing the data, and literature. By acquisition of knowledge from experts, you can create transparent systems that can be expanded[48]. There may also be problems with the acquisition of knowledge from experts, including that experts are not always available and their knowledge is incomplete, episodic, and time-varying [48]. On the other hand, in case of increased number of variables and volume of data, the extraction of knowledge from data can be appropriate and reduce the complexity of the system [49]. Extracting knowledge from data also faces a series of structural issues, including selecting relevant features and finding an effective partitioning of the input domain [50]. Therefore, in order to cope with the problems of each of the knowledge extraction methods, it appears necessary to use a combination of these methods.

The results of this study showed that the median accuracy of the fuzzy rule-based methods was 91%, and the median accuracy of other fuzzy methods was 90%, indicating the high accuracy of these systems in diagnosis of MSDs. In line with these results, Pombo et al., in a review study, also concluded that in the field of medical diagnosis, three methods of fuzzy logic, Bayesian networks, and logistic regression had the highest accuracy (100%) compared to other knowledge modeling methods [17]. A number of studies have also shown that systems that use fuzzy logic for diagnosis and risk assessment of cardiovascular diseases, diabetes, lung cancer, diseases related to the lymph system, thyroid disease and hepatitis, had the highest accuracy in comparison with other methods, including C4.5, Naive Bayes, linear discriminant analysis, artificial immune recognition system, and neural network [51–58]. Therefore, it can be concluded that fuzzy logic is a suitable method for designing a diagnostic CDSSs knowledge base.

The results of this study showed that the most frequent membership functions used in the included studies were triangular and trapezoidal functions. Jin Zhao et al. evaluated the influence of the various types of membership functions on the performance of the system and showed that triangular membership functions had the best performance, and the trapezoidal membership functions had a very close performance to the triangular membership functions [59]. Also, the implementation of triangular membership functions is very simple because they consist of simple straight line segments [59]. The findings of another study also confirmed that triangular and trapezoidal membership functions perform better than other membership functions [60]. It is also shown that Gaussian membership functions have poorer results than triangular and trapezoidal functions [61].

The fuzzy inference mechanism in most studies whose inference was mentioned (71%) was the Mamdani method, and only one study has used the Sugeno method whose system design method was the ANFIS [35]. The results of the studies comparing these two methods showed that Sugeno had a better performance than the Mamdani method[62–64]. Blej et al. compared these two methods in real time scheduling systems and showed that both methods had similar performance except in cases where the Sugeno method allowed the system to work at full capacity [63]. Marzuki et al. compared these two inference methods to measure heartbeat based on ECG signal, indicated that the number of rules required by the Mamdani system was more than the Sugeno system [64]. This indicates that the Mamdani system is more complex and requires more time to provide the outcomes. So Sugeno system is better in relation to the number of correct classification, sensitivity, and processing time of the system than the Mamdani. It is recommended that further studies investigate the effect of using these two inference methods on the accuracy of diagnostic CDSSs.

This study has some strengths and limitations. One of the strengths of this study was searching four important databases (i.e. Medline, ISI Web of Science, Scopus, and Cochrane) which lowered the possibility of missing relevant studies. We also did not apply any time limit in the search. Of the limitations of this study was the non-inclusion of papers presented at conferences (due to the lack of their full text) and papers in non-English languages. Consequently, there is the probability of missing a number of related studies.

The results of this study showed that Fuzzy CDSSs have high accuracy for diagnosis of MSDs. Hence, these systems can be used by specialists to diagnose such disorders. In order to extract the knowledge of these systems, it is better to use a combination of three methods of acquisition from experts, analyzing the data, and literature. Before designing these systems, their implementation challenges need to be considered, too, and appropriate solutions are to be predicted for their implementation in clinical environments. Given the problems associated with the implementation of these systems, it is recommended that they are used at least as an educational tool for medical students.

No studies have developed fuzzy CDSSs to help diagnose the congenital/hereditary, neoplasm of musculoskeletal tissue, and idiopathic disorders. It is recommended that these systems be designed for the above-mentioned diseases in future studies. Considering that fuzzy CDSSs were only examined in the diagnosis of MSDs in this study, it is recommended that these systems be considered for prediction, screening and risk assessment of the MSDs too.

5. Conclusions

In general, fuzzy CDSSs have a high degree of accuracy in diagnosis of MSDs. Despite the high accuracy of these systems, their implementation has so far been limited in the clinical environments due to the implementation challenges. Among MSDs categories, fuzzy CDSSs are more developed to diagnose inflammatory/infectious disorder of the bone and joint. To acquire knowledge for fuzzy CDSSs to diagnose MSDs, one of the following three methods or a combination of them can be used (knowledge acquisition from experts, dataset, and literature). In case of using a combination of these knowledge acquiring methods, these systems will have a strong knowledge base. To design of knowledge base for CDSSs to diagnose MSDs, rule-based methods are used more than other fuzzy methods.

Conflict of interest

The authors have no conflict of interests to declare.

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Supplementary materials

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