Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature and classification

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ARTICLE INFO

ABSTRACT

This paper presents a systematic review of the literature and the classification of fuzzy logic application in an infectious disease. Although the emergence of infectious diseases and their subsequent spread have a significant impact on global health and economics, a comprehensive literature evaluation of this topic has yet to be carried out. Thus, the current study encompasses the first systematic, identifiable and comprehensive academic literature evaluation and classification of the fuzzy logic methods in infectious diseases. 40 papers on this topic, which have been published from 2005 to 2019 and related to the human infectious diseases were evaluated and analyzed. The findings of this evaluation clearly show that the fuzzy logic methods are vastly used for diagnosis of diseases such as dengue fever, hepatitis and tuberculosis. The key fuzzy logic methods used for the infectious disease are the fuzzy inference system; the rule-based fuzzy logic, Adaptive Neuro-Fuzzy Inference System (ANFIS) and fuzzy cognitive map. Furthermore, the accuracy, sensitivity, specificity and the Receiver Operating Characteristic (ROC) curve were universally applied for a performance evaluation of the fuzzy logic techniques. This thesis will also address the various needs between the different industries, practitioners and researchers to encourage

more research regarding the more overlooked areas, and it will conclude with several suggestions for the future infectious disease researches.

1. Introduction

An infectious disease can be defined as a situation that is created by the incursion of a human body by harmful agents which will in turn hurt the body and may spread to other people as well [1]. Infectious diseases are the major cause of illness and death for any given population [2,3]. Human Immunodeficiency Virus infection and Acquired Immune Deficiency Syndrome (HIV/AIDS), Severe Acute Respiratory Syndrome (SARS), H1N1 influenza and Poliomyelitis are examples of an infectious disease [3,4]. While globally the incidence of the infectious disease varies greatly between countries, in the 21st century, the main incidences are hand-foot-mouth disease, Hepatitis B, and Tuberculosis [3]. These diseases have a significant impact on the global health and economies [5]. Despite numerous valuable achievements regarding the procedures for preventing and controlling of various diseases, infectious diseases remain a massive threat to a population's well-being [6]. Aspects such as the increasing in antimicrobial resistance, increase in population and environmental changes are important in an infectious disease transmission [7]. Of 57 million mortality reported per year throughout the world, 14.9 million were related to infectious diseases; which represent more than 25% of the overall deaths [3].

Additionally, clinical diagnosis and detection of the contaminated population are critical elements in controlling and supervising an infectious disease [8]. For the diagnosis of different diseases, there are different essential criteria that should be interpreted by the caregivers [9]. In a clinical situation, an analysis physician combines a patient's medical history, clinical symptoms, physical examination and laboratory findings [10]. Due to the elusive and complex nature of clinical decision-making, they may be accomplished with unwanted errors [11].

In other word, medical diagnosis is an error-prone process, which occurs as the result of logical thinking [10]. Mathematical models are essential means for demonstrating the cause and effect relationship and evaluating the evidence for decisiveness regarding infectious diseases [12]. Computer-aided methods have the potential for examining the complexity of an infectious disease dynamics [11,12]. Computational tools are essential for understanding epidemiological patterns in a disease outbreak [13]. For handling the uncertainty of decision-making, studies have tried to explain the decision-making process in a medical setting by using the Boolean or Binary structure [11].

Fuzzy logic is considered as a vigorous technique for modelling ambiguity in medical practice [14]. In medical field, most medical concepts are fuzzy [15,16]. These concepts usually are difficult to formalize and measure [17]. Fuzzy logic is making a decision in an inaccuracy, uncertainty and incompleteness environment [14]. Fuzzy methods deal with the classes whose boundaries are unclear and elusive [18]. Fuzzy logic concepts were introduced in 1965 [10]. The medical field was one of the first fields in which fuzzy theory was implemented [19]. Fuzzy classes are given a degree of membership that is intermediary between 0 and 1 [18].

Some of the cases for a medical use of the fuzzy set theory are the MYCI, INTERNIST and DOCTORMOON applications [10,20]. Therefore, for these application methods, different types of research have been conducted in the disease diagnosis field. So, the major objective of the current study is to examine the researches in which fuzzy logic techniques have been applied in infectious diseases so to determining its trends and methods, through the processes of conducting a Systematic Literature Review (SLR). The current thesis is structured in the fallowing order. Section 2 exemplifies the procedures or the methodology of the current SLR, Section 3 will present a complete report of the current systematic review. Section 4 will be dedicated to the discussion of this research. Section 5 will be dedicated to the implications of this study, its future research prospects and to the limitations of this evaluation and the last section will be the conclusion.

2. Methods

2.1. Research questions

We carried out an SLR to define the influence of using the fuzzy logic methods in infectious diseases. The three main questions of this SLR are as follow: (RQ1) which domain of an infectious disease was more interesting in past researches? (RQ2) Which fuzzy methods were more dominant in infectious disease data analysis? (RQ3) Which performance evaluation methods were more frequently applied in previous reviews?

2.2. Inclusion and elimination conditions

This systematic review was done according to the Systematic Reviews and Meta-Analysis (PRISMA) method. Among the achieved studies, we have used papers that have at least one of the subsequent criteria: language in English, time is from the year 2005 to 2019, original articles and conference papers, human disease and all kinds of infectious disease, and elimination criteria: articles written in other language other than English, diagnosis, treatment and follow up of animal disease, book, book chapter, letter to editor, brief reports, thesis and review articles, time is before the year 2005, articles related to environmental health, water and air pollution and articles related to spatial data analysis.

2.3. Search mechanism

Based on our research questions, some of the digital databases were scrutinized for the required papers; PubMed, Science Direct, Web of Science and Scopus were all included

in this search. In this SLR, the survey was restricted to the conference papers and journals that were published between the years 2005 and 2019. In searching the databases, the search string should produce enough coverage of papers in an acceptable size. In this SLR, to determining the search string, the keywords pertinent to the study questions were achieved and the synonyms that were used to match the keywords were established. The Boolean OR structure was applied to associate synonym words while Boolean AND was applied to join the main parts to each other. The full set of search string in this SLR fitted is as follows: (Infectious diseases OR communicable disease OR transmissible disease) AND (Fuzzy logic) AND (Disease OR Diagnosis OR treatment) AND (Model* OR algorithm* OR technique* OR rule* OR Method*).

2.4. Extraction of study characteristic

For the gathering of the relevant information from all the eligible articles, a data extraction method was used for getting the detailed answer of the research questions.

(RQ1) Which domain of an infectious disease was more interesting in past researches?

(RQ2) Which fuzzy techniques were more dominant in an infectious disease data analysis?

(RQ3) Which performance evaluation procedures were more frequently applied in the previous reviews?

To answer the research questions and to produce the extracted data, numerous methods were used. Generally, a narrative combining approach to answering different research questions was applied. Furthermore, various visualization techniques such as tables and charts were used according to the research questions.
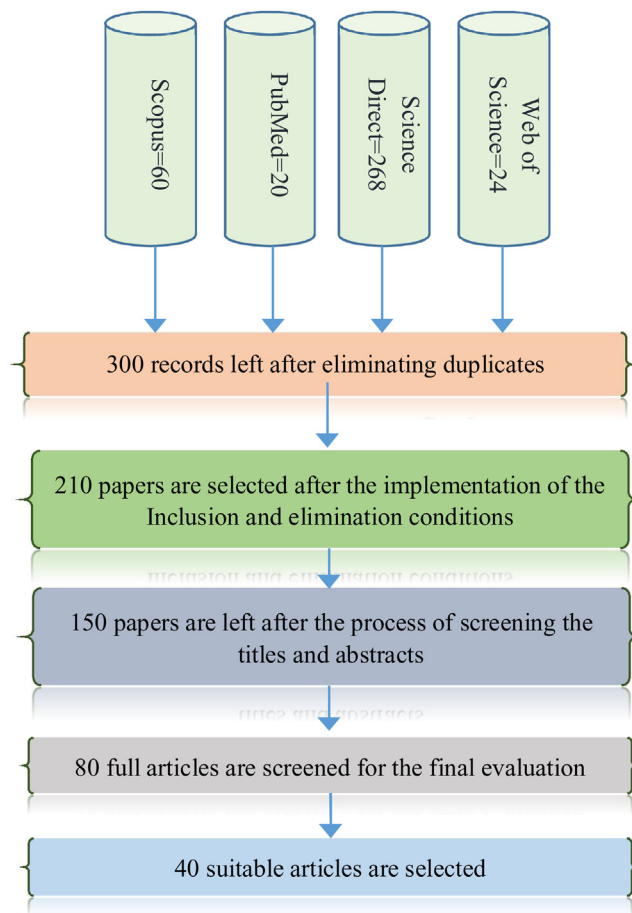
3. Result

Current part is dedicated to the outcome of the current SLR. First, we will demonstrate an overall description of the outcome of selecting the appropriate studies; and then, all the obtained outcomes will be categorized for each study questions independently.

3.1. Summary of the paper selection process

By searching for the four aforementioned databases, the 372-candidate paper was removed as shown in Fig. 1. Then, based on using the exclusion conditions, 162 studies were excluded. The other 210 articles were investigated meticulously to choose relevant studies.

By reviewing the title, abstract and the keywords, merely papers that have at least one of the inclusion measures were used. Eventually, 40 papers were used to get an answer to the research questions and data extraction for this Methodical Evaluation.

Fig. 2 is showing the distribution of eligible papers per year. According to the diagram below, the frequency of papers relevant to the use of fuzzy logic in an infectious disease was roughly stable during the first 5 years. However, as shown in the next chart, there is a persistent trend in the number of

Fig. 1 – PRISMA diagram showing the screening process used for the selected papers.

papers, peaking at a maximum of 7 articles in 2012 and 2017. This figure demonstrates that the quantity of papers has increased from 2005 to 2012.

Moreover, the frequency of papers published in each year has increased from 2 articles in 2005 to 7 articles in 2017. Furthermore, from 2005, the rate of publications has increased notably. Moreover, the number of papers from 2012 to 2016 has decreases, and then increased in 2017.

Finally, the spread of the relevant articles based on a journal or conference, has been explained in Table 1. Based on the obtained results Expert Systems with Applications journal was used by researchers for publishing their studies in the 9.6 percent of instances.

3.2. RQ1: Which domain of an infectious disease was more interesting in past researches?

Articles related to the precise domain of fuzzy methods application in an infectious disease, which have been considered from the past section, are summarized in the following section.

Fig. 3 illustrates the distribution of numerous fuzzy techniques that have been used in an infectious disease data analysis. Based on this figure, the results revealed that the
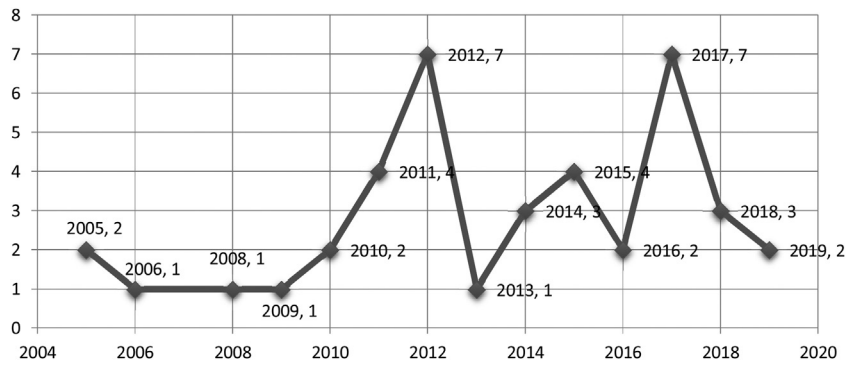
Fig. 2 – Spread of relevant articles per publication year.

Table 1 – Distribution of papers according to journal and publication type.			
Journal title	Count	Journal or conference paper	Percentage
Computational and Mathematical Methods in Medicine	2	Journal	6.4
BMC Medical Informatics and Decision Making	2	Journal	6.4
Intelligent Decision Technologies	1	Journal	3.2
Springer Nature Singapore Pte Ltd.	1	Journal	3.2
Bulletin of Mathematical Biology	1	Journal	3.2
Journal of the National Science Foundation of Sri Lanka	1	Journal	3.2
Expert Systems With Applications	1	Journal	3.2
Journal of Infection and Public Health	1	Journal	3.2
Micron	1	Journal	3.2
Expert Systems with Applications	3	Journal	9.6
Informatics in Medicine Unlocked	2	Journal	6.4
Springer Plus	1	Journal	3.2
International conference on knowledge-based engineering and innovation	1	Conference paper	3.2
Artificial Intelligence in Medicine	1	Journal	3.2
The 5th International Conference on Electrical Engineering and Informatics 2015	1	Conference paper	3.2
IEEE Transactions On Fuzzy Systems	1	Journal	3.2
TELKOMNIKA	1	Journal	3.2
Fuzzy Sets and Systems	1	Journal	3.2
International Conference on "Computational Intelligence and Communication Technology" (CICT 2018)	1	Conference paper	3.2
BMC Systems Biology	1	Journal	3.2
IET Systems Biology	1	Journal	3.2
Archives of Oral Biology	1	Journal	3.2
IEEE Trans. Syst. Man Cybern	1	Conference paper	3.2
Journal of the medical system	2	Journal	6.4
International Conference on Computer Information Systems and Industrial Management Applications (CISIM)	1	Conference paper	3.2
Computer methods and programs in biomedicine	2	Journal	3.2
Journal of Clinical Monitoring and Computing	1	Journal	3.2
Journal of King Saud University – Computer and Information Sciences	1	Journal	3.2
Iranian Journal of Medical Physics	1	Journal	3.2
Applied Computing and Informatics	1	Journal	3.2
2011 Ninth International Conference on Software Engineering Research, Management and Applications	1	Journal	3.2
IEEE Transactions On Information Technology In Biomedicine	1	Journal	3.2

critical application domain of the fuzzy methods in an infectious disease were relevant to dengue fever (15% of papers), hepatitis and tuberculosis (10% of papers). In addition, the other papers were related to diseases such as pulmonary infection (7.5% of papers), Urinary Tract Infections (UTIs), Human Immune deficiency Viruses (HIV) and Meningitis (5% of papers). For all the other diseases, there is one paper per each disease (2.5% of papers).

Appendix A, Table A1 lists eligible articles according to the specific type of disease, their objective, their inward and outward variables and findings.

As shown in Fig. 3, the distribution of the different fuzzy methods in various disease data analysis was as fallows. In articles published for dengue fever, 33.33% of the papers applied fuzzy set theory and the Adaptive Neuro-Fuzzy Inference System (ANFIS) method in data analysis while
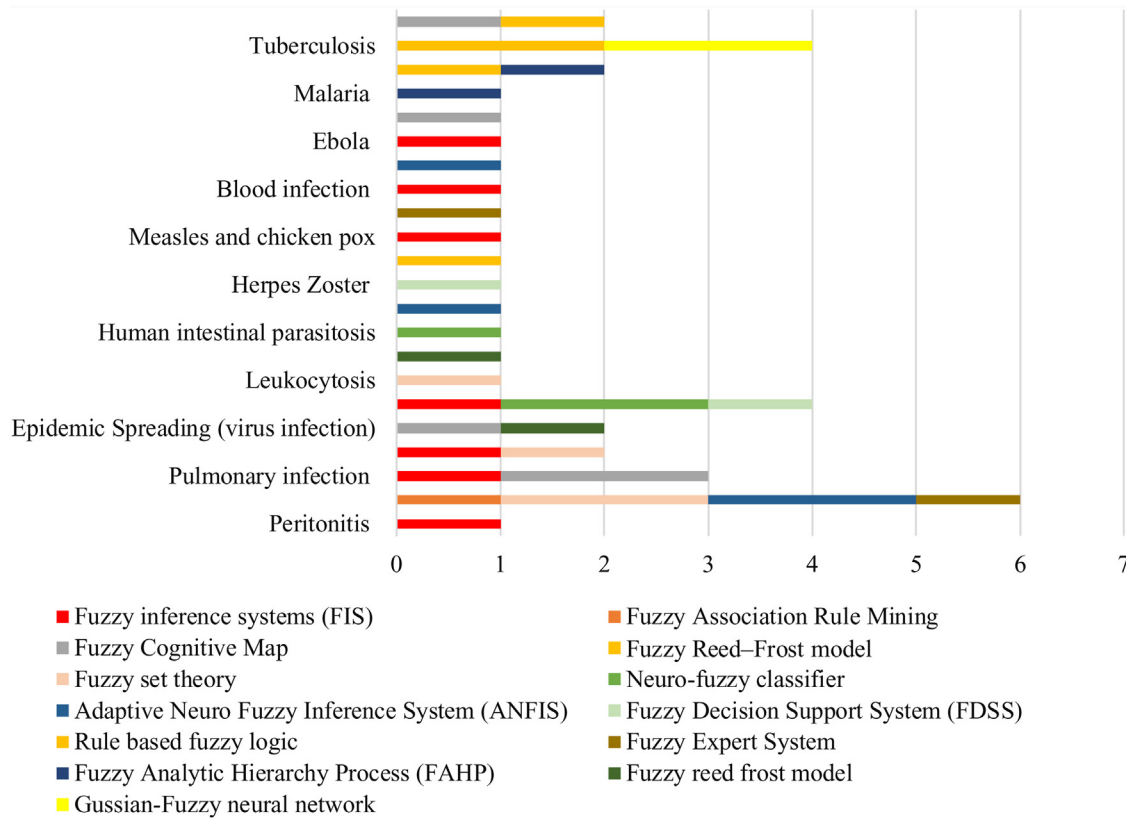
Fig. 3 – Distribution of papers according to disease type (X axis) and the fuzzy logic methods (Y axis) used.

16.6% of the papers used association rule mining. 50% of selected papers that related to hepatitis, employed Neuro-Fuzzy classifier as a fuzzy technique, while the other 50% were devoted to fuzzy inference system and Fuzzy Decision Support System (FDSS). Furthermore, in tuberculosis studies, 50% of the papers used rule-based fuzzy logic and 50% of the papers applied the Gaussian-Fuzzy neural network method.

3.3. RQ2: Which fuzzy techniques were more dominant in an infectious disease data analysis?

Fig. 4 shows the distribution of the fuzzy logic techniques per year. From 2004 to 2007 few techniques were used such as fuzzy inference system, rule-based fuzzy logic, ANFIS and fuzzy expert system, whereas after that a number of different and novel techniques such as; Fuzzy Analytic Hierarchy Process (FAHP), Fuzzy Reed-Frost model, genetic neuro-fuzzy and Fuzzy Decision Support System (FDSS) were used in different studies. The most interesting outcome was that among all the varies used techniques of fuzzy logic in the studied papers, rule-based fuzzy logic; ANFIS, FIS and fuzzy cognitive maps were more frequently used in various disease data analysis.

3.3.1. Fuzzy inference systems (FIS)
Fuzzy inference systems are increasingly becoming more predominant in the area of fuzzy logic methods where 15% of the selected papers in the current SLR are related to this

particular method. Fuzzy inference systems are used for the processes of mapping the inward variables to appropriate outward [21,22]. Fuzzy inference process incorporates three key concepts: the membership functions, the fuzzy set operations, and the inference procedures [23]. A fuzzy inference system can be divided mainly to four portions as follows: fuzzification, weighting, assessment of inference procedures, and the de-fuzzification [24].

DragoviT et al. utilized the fuzzy inference system to decide the probability of having peritonitis in patients. By using this system, the fuzzy rules enable the automation of the clinical decision making process in an imprecise and complicated conditions [25]. Urinary Tract Infections (UTIs) are considered amongst one of the utmost predominant bacterial infections.

Ibrisimovic et al. has suggested a FIS fuzzy model, to provide the necessary support that the caregivers need for explaining the aftermath of a microscopic urine analysis. To create the model's various variables such as the Colony Forming Units (CFU), White Blood Cells (WBC) and the Red Blood Cells (RBC) as well as the turbidity of urine specimen used for inward variables, and the risk of a UTI as an outward variable. The end result has revealed that the use of the fuzzy methods simplifies and secures the clarification of urine analysis [26].

Putra and Munir proposed a method for diagnosis of measles, German measles and varicella. The data for those diseases were used because of the similarity of their infection mechanism and symptoms. A built fuzzy inference system
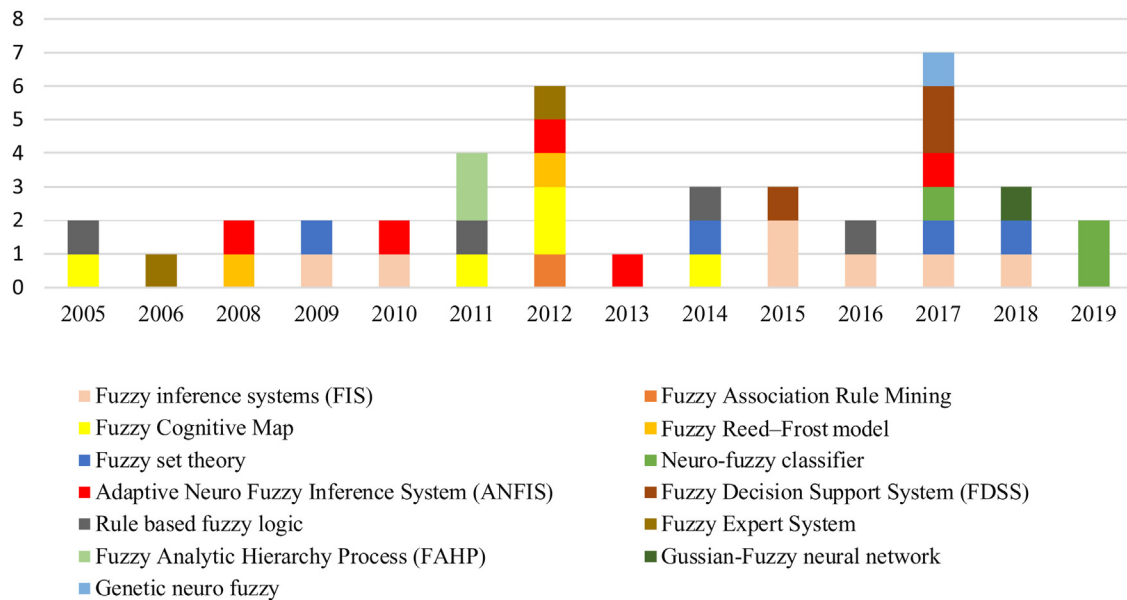
Fig. 4 – Yearly distribution of the different fuzzy logic methods per year.

takes in the inward variables that represent the possible symptoms that may appear in each disease. Cough, runny nose, sore throat, conjunctivitis, Koplik's spot, diarrhea, headache, swollen neck or ear, loss of appetite, malaise, pimples/crust skin, joint pain used as inward variables. The application effectively identified 19 out of 25 accurate diseases throughout its testing stage [27].

3.3.2. ANFIS

The ANFIS method was proposed by Jang and its notions then were used in other fields [22]. This method works by setting a list of features by using an amalgam of learning rules which will incorporate the back-propagation incline in error digestion and a tiniest squares method. This method can be implemented as the basis for creating a set of IF-THEN guidelines with suitable association of functions to brand the inward and outward variables [22]. ANFIS method has been notably successful in disease diagnosis in the past few years. As an example, the major groups of hepatitis in human beings are hepatitis A, hepatitis B and hepatitis C with the main symptoms being malaise (a common sick feeling), fever, and muscle pain, loss of appetite, nausea, vomiting, diarrhea, and jaundice. Viral hepatitis disease can be diagnosed by blood test analysis and interpretations. Dogantekin et al. developed an ANFIS system to be used for hepatitis diagnosis. The precision achieved in this automated system of diagnosis was at about 94.16% [28].

Faisal et al. conducted a research using an adaptive neuro-fuzzy inference system to diagnose a dengue fever. The general precision of the developed method is 86.13% with its sensitivity being at 87.5% and its specificity being at 86.7% [29]. This method was used in the Campisi research as well to determine the amount of the risk factors of an infection disease in relationship with Oral Candidiasis (OC) [30].

Additionally, Shariati has recommended a method of diagnosis for both hepatitis and thyroid diseases. The researchers in this study compared the outcome of the ANFIS technique with the Support Vector Machine (SVM) and the artificial neural networks techniques. Then, they demonstrate that this technique had an improved outcome in being a precise diagnosis in comparison with the previous techniques [31].

3.3.3. The rule based fuzzy logic system

The information in a fuzzy rule-based system is typically represented by using an IF-THEN statement. Rule-based Fuzzy logic includes two portions: the precursor portion are the relevant conditions which are known as the inward variable(s), and the subsequent portion which expresses the outward variable(s).

Mamdani and Sugeno are two different types of fuzzy rule-based systems. In the Mamdani technique, the precursor, as well as the subsequent section, comprises fuzzy statements that reveal the value of the variables, while in Sugeno method, the subsequent portion displays a nonlinear affiliation among both the inward and outward variables [32,33]. Because of the complex nature of the numerous diseases, this technique can improve the infectious disease diagnosis and the treatment of such diseases as HIV and tuberculosis. Based on this, Sloot et al. efficiently used rule-based fuzzy logic to uncover the drug-resistance in HIV patients [34].

Furthermore, Semogan et al. has created a clinical decision supporting system based on the fuzzy logic and the rule-based model that determine different classes of tuberculosis to assess respiratory diseases. In this system variables such as cough, cough duration, body temperature, fever duration, sputum discoloration, nose sputum, afternoon chills, night sweats, weight loss, and loss of appetite have been used in the diagnosis [35].

3.3.4. The fuzzy cognitive map technique

The Fuzzy Cognitive Map (FCM) is a modelling technique that defines the connections between concepts such as variables, the inwards and the outwards by the methods of previous knowledge and experience. Kosko has introduced FCM in 1986. FCM is usually used to demonstrate the cause and effect relationship between the different concepts in a given system. FCMs are used in numerous fields such as in engineering, error detection and medicine [36,37]. In this regard, Mei et al. has applied FCM to describe how factors such as people's emotions and cognition functions influence each other to create epidemic infection [38]. FCM was also used by the Mago et al. research to develop the required knowledge-based structure used for recognizing the specific causes and the symptoms of meningitis disease in children. This system can be implemented as a dependable instrument in supporting the physician's to better their decision making processes [39].

3.4. RQ3: Which performance evaluation techniques were more frequently applied in the previous reviews?

Performance evaluation procedures are among the furthermost significant indicators for determining the quality of the artificial intelligence techniques [40]. Overall, performance evaluation procedures are classified into two main types; the first being the single scaler techniques and second being the graphical techniques.

The sensitivity, specificity and the accuracy indicators are grouped into the single scaler techniques. Receiver Operating Characteristic (ROC) curve, cost-line, and lift graph are clustered together in graphical methods. Anyhow, graphical methods cannot simply be clarified and analyzed as single scalar method [41–43]. Fig. 5 indicates the most noticeable performance evaluation indicators used in eligible papers.

For the current SLR, most qualified studies did not use any kind of indicators for analyzing the performance of the fuzzy techniques. Among the fuzzy techniques, ANFIS and FIS techniques were evaluated by single scaler techniques and graphical evaluation techniques.

4. Discussion

The major objective of this SLR was to select and examine the various studies relevant to the employment of the fuzzy logic techniques in an infectious disease. In this regard, 40 studies were selected and analyzed from an original number of 372 candidate studies. This section is dedicated to the discussion of the major findings of this study.

4.1. RQ1: Which domain of an infectious disease was more interesting in past researches?

In last few years, it has been obvious from the results of analytic studies conducted in our research that there is a growing interest in studying the relevance of the fuzzy logic techniques for an infectious diseases diagnosis applications. The studies have shown that there is an increase in the number of published articles from 5% in 2005 up to 17.5% of the evaluated papers in 2017. This growing trend may prove the popularity of the fuzzy techniques between different academic papers and its valuable effects in identifying the infectious disease trends. Additionally, 13 different fuzzy logic techniques have been used in the evaluated papers. From a medical point of view, in Fig. 3 we found that the main application domain of fuzzy logic in infectious disease was related to dengue fever, hepatitis and tuberculosis respectively. The other noticeable outcome that we have found was the
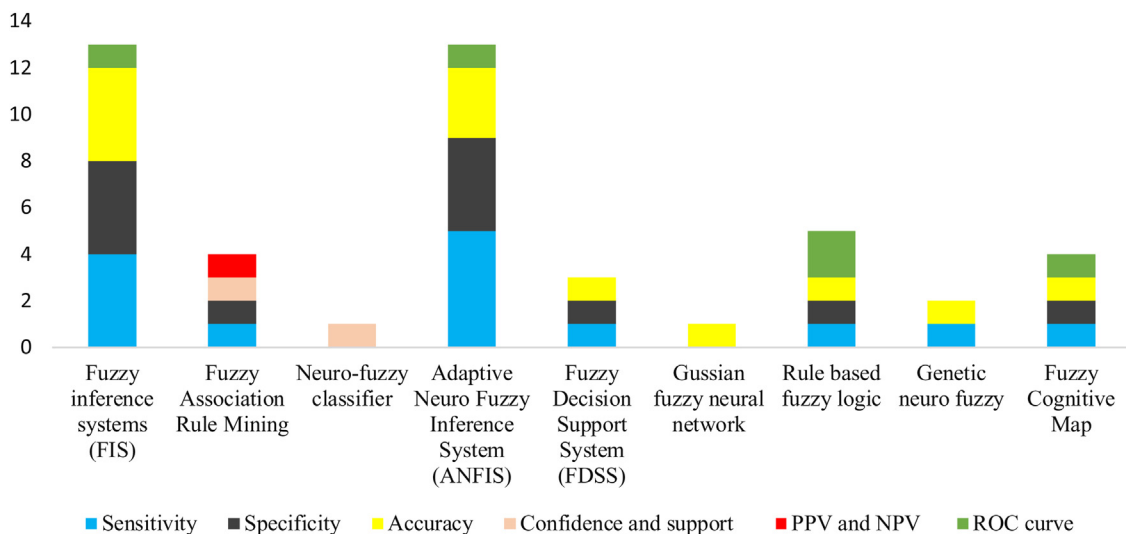

Fig. 5 – Papers distribution based on the performance evaluation indicators.

fact that the evaluated papers were very diverse in terms of disease types.

Because of the big impact on global health by infectious diseases, determining the different features of these diseases are a valuable source for improving our knowledge and ability to predict how a disease will spread in a population [2,3]. The ability to comprehend and control an infectious disease can be obtained by the usage of mathematical models [44]. The newly arising infectious agents such as HIV, the Severe Acute Respiratory Syndrome (SARS), the Mid-Eastern respiratory syndrome (MERS) coronaviruses; the West Nile Virus; the Nipah virus; the drug-resistant pathogens; novel influenza A strains and the Ebola virus outbreak were considered as big challenge to health in the recent century [6]. Using computer-aided diagnosis techniques like the fuzzy logic technique can be useful in determining the main factors associated with the infectious diseases occurrence and epidemics.

Regarding this, in another field of research in relationship to the vaccination strategies for infectious diseases it has been shown that infectious diseases such as influenza have a seasonal pattern in which case mathematical techniques such as the fuzzy logic techniques is considered a vital instrument in the process of forecasting the viral development from one year to another. This technique can also deliver the required scientific confirmation which will help us decide the amount of vaccine treatment, its efficiency, its financial costs and its pattern of contact in any given population [6,45,46]. It has been shown that the fuzzy based techniques have an essential part in the determination of infectious disease outbreaks. As an example for that, we have the HIV outbreaks, these techniques can identify at what time a viral transmission has occurred, its outbreak stage and the sexual behavior pattern of the specific population in which a disease is spreading. Moreover, the infectious diseases annihilation and elimination techniques dictate that the transmission process itself has to be the target not the disease. Regard this, the data sources are typically scattered and the collective effect of the numerous control techniques are complex and are dependent on the rate of transmission [47].

4.2. RQ2: Which fuzzy techniques were more dominant in an infectious disease data analysis?

As shown in Fig. 4, there is a various number of fuzzy techniques employed in the chosen papers. Based on this studied section we can mostly classify the fuzzy techniques into four main classes; the fuzzy inference system, the rule-based fuzzy logic, ANFIS and the fuzzy cognitive map. The fuzzy inference system and the ANFIS technique were used as shown in 17.5% and 12.5% of candidate papers, respectively. FIS is based on the 'IF-THEN' rules and it can be used to predict the behavior of a various uncertain situations [48]. As seen in the distribution of the studied articles, we can say that fuzzy techniques are efficient means for modelling unclear disease conditions such as in the case of transmissible disease diagnosis.

Additionally, in the last few years, there has been substantial interest amongst the researchers to apply the ANFIS technique in the case of an infectious disease. ANFIS combines the positive effects of both ANN and FIS in an

influential tool for disease diagnosis. This technique does not require excessive knowledge in the modelling and training system. These techniques are usually valuable for the situation, which are in many cases complicated, with a non-linear behavior pattern. This work approach has created a relationship between the inward and the outward features by the means of the neurons [49].

4.3. RQ3: Which performance evaluation procedures were more frequently applied in the previous reviews?

Performance evaluation procedures are usually employed as a valued method in determining the quality of the numerous fuzzy techniques [40]. As shown in Fig. 5 in the current SLR, amongst the single scaler techniques, the sensitivity, specificity and the accuracy are frequently utilized in the evaluation of a developed technique. Additionally, in graphical evaluation techniques, the ROC curve was the other measure of performance evaluation that was used in the adequate papers. These indicators are to be considered significant when reporting and assessing a diagnostic technique. Scientists have to provide suitable information about the sensitivity, specificity, and the projected values when describing a computer based diagnostic technique end results and this information must contain how those metrics are concluded and also what are its appropriate interpretations [43,49].

Although those indicators are promising in qualified studies, nonetheless, they typically generate an inadequate image of the indicators performance and thus it is possible to lose a certain amount of valuable information. Moreover, it is possible that the employment of a single-scaler technique will not identify the full scope of a performance assessment. Therefore, a comprehensive and dependable assessment must reflect all the numerous parts of performance distinctive quality.

5. Future implications of the research and the study limitations

In this methodical review, the studies related to the employment of the fuzzy logic techniques in an infectious disease were assessed, and depending on the acquired outcomes, we can notice an interest amongst the researchers regarding this specific field of research. In last few years, a large number of the transmissible diseases that were supposed to be eliminated have made a comeback. Certain factors such as manufacturing, agricultural practices, wars, changes in life-styles, development and urbanization, and environmental change are all effective in the appearance and reappearance of an infectious disease [50]. This SLR's result demonstrates that even though these are the most of the infectious diseases that were investigated, but there is still more area that needs to be covered. Nevertheless, more work should be carried out on the appearance and reappearance diseases domains such as H1N1, SARS, Zoonosis and the Rift valley fever.

Internationally, there is a lack of an integrated framework for reporting infectious disease [51]. Additionally, an infectious diseases information system has an inadequate support for data analysis and generating predictive techniques centered on artificial intelligence. An integrated analytical framework

that offers functions as in a progressive data analysis capability and a visualization support is of a critical importance [51,52]. There is serious need for creating an atmosphere for collecting, distributing, reporting, assessing, and picturing the infectious disease data and to provide support for decision-making tools regarding disease prevention, recognition, and controlling [53,54].

Infectious disease observation and controlling has demanded an interdisciplinary work. To have the ability to achieve those objectives, the employment of Geographic Information Systems (GIS), three-dimensional information analysis, machine learning and visualization applications and techniques became a must. Because of the significance of the infectious diseases at the global level, it is essential to simultaneously develop an incorporated infectious disease dataset and to make the specialized analytical and diagnostic methods all at the same time.

Additionally, there was slight conversation in the incorporated literature about three-dimensional information analysis for an infectious disease occurrence. Three-dimensional information evaluation techniques may be useful in determining the concentration pattern of a disease occurrence and to make the required association from the determined patterns to the measureable procedures [55,56].

Furthermore, the social networks information study has facilitated the evaluation of the association amongst the population in a particular social setting. Methods that correlate spatial and social network data analysis are unusual but have the capacity to promote the determination of a spreading progress of an infectious disease [57]. Or we can say, the deployment of a unified spatial and social network structure to define the spreading of an infectious pathogens in a given populace will allow insights into both the understanding to the disease method of distribution and the possible process associated with the observed patterns. Since there are various studies regarding social media information analysis, we recommend the use of this dataset for the prediction of an infectious disease epidemic.

This research has its limitations. Even with the use of a broad search approach, some of the publications regarding the fuzzy logic deployment in an infectious disease could not be recovered, as in the case of grey literature and reports that were not published in surveyed digital databases, which we have reviewed. Thus, it is recommended that additional SLR papers should be carried out to go through the other noticeable databases. Additionally, some studies did not report clearly on the performance assessment technique. In conclusion, only the English language publications were included, therefore future studies could be expanded to incorporate relevant papers which are published in other languages.

6.   Conclusion

In this study we have identified, classified, and defined the use of the fuzzy logic techniques in infectious diseases. 40 studies were scrutinized and the main conclusions can be briefed as follows: (1) the key application field of the fuzzy logic in an infectious disease was related to dengue fever, hepatitis and tuberculosis, (2) amongst the fuzzy logic techniques fuzzy inference system, rule-based fuzzy logic, ANFIS and fuzzy cognitive map are commonly used in many studies, and (3) the major performance evaluation indicators such as the sensitivity, specificity, and the accuracy the ROC curve is employed. In addition, this study highlights the absence of an integration of infectious disease information systems in order to provide a valuable datasets in this domain. Additionally, using machine learning and visualization applications for information analysis is essential.

Even though in the current SLR there is a diversity of infectious diseases that are investigated, there is only one article per each disease. There is additional need to use the fuzzy logic methods for infectious disease detection and prediction. It appears that one of the causes for a limited number of relevant articles to infectious diseases is in the difficulty in obtaining adequate research data.

Finally, we expect that a mounting number of infectious diseases datasets will be mostly obtainable in the forthcoming years because of raising collaboration amongst medical practitioners and researchers and that this would lead to additional studies of the machine learning techniques that can be useful in this regard.

CRediT authorship contribution statement

Goli Arji: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Hossein Ahmadi:** Methodology, Validation, Writing - review & editing. **Mehrbakhsh Nilashi:** Validation, Supervision, Visualization, Conceptualization, Software, Writing - review & editing. **Tarik A. Rashid:** Conceptualization, Investigation, Validation, Writing - review & editing. **Omed Hassan Ahmed:** Software, Writing - review & editing. **Nahla Aljojo:** Writing - review & editing, Supervision. **Azida Zainol:** Visualization, Validation.

Appendix A

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
					Table A1 – The classification of publications for the fuzzy techniques, their research objectives, their inward and outward variables and their main conclusions.			
1	Ivana DragoviT [25]	2015	Peritonitis	Fuzzy Inference Systems (FIS)	Developing a fuzzy inference system for diagnosing of peritonitis.	Fever, Number of leukocytes, Abdominal ache, Cloudiness of effluent, Microbiological culture.	Peritonitis	The proposed FIS technique enables physicians to easily diagnosis peritonitis.
2	Anna L Buczak [58]	2012	Dengue	Fuzzy association rule mining	Providing a fuzzy association rule mining technique to determine correlations between clinical, meteorological, climatic, and socio-political data for dengue fever diagnosis.	Rainfall, Temperature, Altitude, Demographics.	Dengue	Developing a new approach for dengue outbreak prediction and has the potential to be extended to other environmentally infections.
3	Elpiniki I. Papageorgiou [59]	2011	Pulmonary infection	Fuzzy cognitive map	Fuzzy cognitive map to the assessment of pulmonary infections.	Dyspnea, Cough, Rigor/chills, Fever, Loss of appetite, Debility, Pleuritic pain, Hemoptysis, Oxygen the requirement, Tachypnea, Acoustic characteristics, Glasgow Coma Scale (GCS), Systolic Blood Pressure, Tachycardia, Radiologic evidence of pneumonia, Radiologic evidence of complicated pneumonia, PH, Comorbidities, Age.	Risk of pulmonary infection	FCM can handle efficiently with uncertainty in modelling in pulmonary infection.
4	Monia Avdic Ibrisimovic [26]	2017	Urinary Tract Infections (UTIs)	FIS	To achieve an improvement in construing the outcomes of the microscopic urine examination by means of fuzzy logic methods.	CFU Count, WBC Count, RBC Count, Turbidity.	Risk of UTI	The fuzzy logic foretells the existence of urinary tract infection in the patient by microscopically examined parameters.
5	Neli R.S. Ortega [60]	2008	Virus infection	Fuzzy Reed Frost model	A new fuzzy approach by means of the Reed Frost model for wide spreading of the infection.	Fever, cough, sneeze and wheeze.	Virus infection	This model create a better way to determining the aspects which might contribute to the spreading of the infection throughout a widespread.

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
6	W.P.T.M. Wickramaarachchi [61]	2018	Dengue	Fuzzy set theory	Developing a weather threat index model by use of fuzzy set theory.	The entire number of the population, The birth ratio of population, The biting ratio of the mosquitoes.	Risk of Dengue fever	This model can be used to suggest the dynamics of infections and the number of infections in a specific time.
7	Malmir [62]	2017	Kidney infection	Fuzzy Decision Support System (FDSS)	Improvement of kidney infection diagnosis by means of FDSS method.	Bad smell urine, Chill and fever, Dysuria, Flank pain bilateral, Flank pain unilateral, Frequency and urgency, Hematuria, Nausea and vomiting, Urine pus.	Risk of kidney infection	The proposed FDSS method is capable of diagnosing diseases with a high level of accuracy.
8	Nilashi [63]	2019	Hepatitis	Neuro-fuzzy technique	Proposing a novel method for the hepatitis diagnosis by ensemble learning.	Age, Gender, Steroid, Antivirals, Exhaustion, Malaise, Anorexia, Liver Big, Liver Firm, Spleen Palpable, Spiders Ascites, Bilirubin, Alk Phosphate, SGOT, Albumin, Protein and Histology.	Hepatitis	The proposed method's outperformance to the Neural Network, ANFIS, K-Nearest Neighbors and Support Vector Machine in this study.
9	Tamalika Chaira [64]	2014	Leukocytosis	Fuzzy set theory	Developing an approach to the segmentation of pathological blood cell images	The microphotographs from blood smears.	Segmentation of leukocyte in blood cell	Based on the result both intervals Type II fuzzy and intuitionistic fuzzy methods have better performance compared to non-fuzzy methods.
10	Tarig Faisal [29]	2012	Dengue	Adaptive Neuro-Fuzzy Inference System (ANFIS)	To develop an ANFIS method to diagnose the risk in dengue fever	Fever, Headache, Dizziness and fainting, Weakness lower limb, Arthralgia, Myalgia, Body ache, Nausea, Vomit, Anorexia, Abdominal Epigastric pain, Chill and rigour, Petechiae Rash, Flush face, Bleeding tendency, Hepatomegaly, Conjunctivitis, and Macular platelete (PLT), hematocrit, (HCT), Aspartate aminotransferase (AST), alanine aminotransferase (ALT) and Hemoglobin (Hb).	Not specified.	The proposed ANFIS model has better performance in comparison of the other methods.

Table A1 (Continued)

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
11	Imke Traulsen [65]	2012	Airborne transmission infection	Fuzzy logic	Use of the fuzzy logic model to predict airborne transmission infection	Downwind farms, Speed of wind, and stability class.	likelihood of infection	Fuzzy logic model demonstrates the similar threat of infection for secondary cases compared to the Gaussian dispersion technique.
12	Esin Dogantekin [28]	2009	Hepatitis	Fuzzy Inference Systems (FIS)	Creating an automatic diagnosis system for hepatitis diagnosis.	Gender, Steroid, Antivirals, Exhaustion, Malaise, Anorexia, Liver big, Liver firm, Spleen palpable, Spiders, Ascites, Varices, Bilirubin, Alk phosphate, SGOT, ALBUMIN, PROTIME, HISTOLOGY.	Die or live	The total accuracy of the developed system was obtained in about 94.16%.
13	Oscar Takam Nkamgang [66]	2019	Human intestinal parasitosis	Neuro-fuzzy classifier	Implementation an expert system to the diagnosis of intestinal parasitoids.	Diarrhea, headache, fever, stomach bloating, dry cough, dry cough, anorexia, bulimia, vomiting, nausea.	Stool exam analysis	The proposed automated system successfully used to stool exam analysis.
14	Dhifaf Azeez [67]	2013	Infections in the emergency department	ANFIS	Developing a model to determining infection in the emergency department by means of ANFIS and artificial neural network.	Age category, Gender, Airway and inhalation, Tachycardia, Bradycardia Sever Pallor, Cold Peripheries, Tachypnea, is uncompleted in full Sentence, One Sided Limb Weakness, Slurring of Speech, Facial Asymmetry, Sever Chest Pain, Perfuse Sweating, Altered Mental Status(drowsy, confused), Sever Intractable Pain, Psychiatric Patient bad-tempered, Chief criticism, Heart ratio, Respiration ratio.	Resuscitation, emergent and non-urgent.	The ANN method had better performance than the ANFIS model in infection diagnosis.
15	Sanaei [68]	2015	Herpes Zoster	Fuzzy Decision Support System (FDSS)	An expert system for diagnosis of herpes zoster based on fuzzy logic.	Perception symptoms, dermatome distribution, age, general symptom, unilateral, recurrence, a variation of size.	Herpes Zoster	Using this expert system have a significant role in the enhancement in diagnosing the disease; decrease severe pain and fall of costs.
16	Bruin [69]	2016	Healthcare-Associated Infections (HAIs)	Rule-based fuzzy logic	Rule-based fuzzy logic in HAIs diagnosis.	Rise body fever, shock, droplet in blood pressure, increased C-reactive protein, leukopenia, and leukocytosis.	Normal, borderline, or pathological	The results showed that the model was helpful in HAI detection.

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
17	Putra [27]	2015	Measles and chicken pox	Fuzzy Inference Systems (FIS)	Diagnosis of children's skin disease by means of the FIS model	Cough, Runny nose, Sore throat, Conjunctivitis, Koplik's spot, Diarrhea, Headache, Swollen neck or ear, Loss of appetite, Malaise, Pimples/crust skin and Joint pain.	Measles, German measles and chicken pox	The proposed model had good performance in disease diagnosis.
18	Mei [38]	2014	Epidemic infection	Fuzzy Cognitive Map	Using FCM method to describe epidemic infection pattern.	Frequent hand washes surrounding disinfection, Mask wearing and preventive medication taking, Crowd avoidance and vaccination.	Infection	Individual decision making against infections can importantly reduce the at-peak number of infected patients.
19	Putra [70]	2012	Dengue	Fuzzy Expert System	Fuzzy Expert System for diagnosing tropical infectious disease	The symptoms of diseases and user response options for dengue fever, Dengue Hemorrhagic I, Dengue Hemorrhagic II, Dengue Hemorrhagic III, Dengue Hemorrhagic IV, Chikungunya, Typhoid Fever.	Tropical Infectious Disease diagnosis	The proposed method has the similarity diagnosis with the expert at 93.99%.
20	Davidson [71]	2006	Microbial hazards in food	Fuzzy expert system	Creating a Tool for Fuzzy Risk Assessment (FRAT) which uses for initial evaluation of microbial hazards in food systems	Early risk level, Effectiveness of post-processing control, Effectiveness of customer preparation, Amount of product contaminated, Recontamination, Frequency of consumption, Proportion of population that consumes the product, Population size, Hazard severity.	Microbial risk assessments in food	This system estimates the risk of microbial hazards in food systems.
21	Raghav [72]	2018	Blood infection	Fuzzy Inference Systems (FIS)	Construct an intelligent FIS model for blood infectious using FIS.	HB, RBC, PC, HCT, MCV, MCH, MCHC, BS.	Blood infection	The suggested model can be used to detect a blood infection in patients.
22	Jayasundara [73]	2017	Dengue	ANFIS	Examination of the combined effect of multiple cytokines that interact dynamically with each other in order to produce a mathematical model to predict the occurrence of Dengue Hemorrhagic Fever.	S1P, IL-1β, TNF-α, PAF and IL-10.	Dengue Hemorrhagic Fever.	The results have shown a unique mathematical method for the evolution of the dengue fever patients with great accuracy.

Table A1 (*Continued*)

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
23	Premaratne [74]	2017	Dengue	Fuzzy set theory	Mathematical modelling of Immune Parameters for the Evolution of Severe Dengue.	Platelet count, NS1 Panbio levels, IgG Panbio levels, and lymphocyte.	Dengue	The results have shown sound precision in dengue fever diagnosis.
24	Khodaei-Mehr [75]	2017	Hepatitis C	Neuro-fuzzy technique	To produce a new intelligent system to control the hepatitis C infection in patients.	Susceptible individuals S (t), exposed individuals with hepatitis symptoms E (t), individuals with the acute infection I(t), individuals undergoing treatment T(t) and individuals with chronic infection V(t).	Hepatitis C Infection	The end results have shown a major decrease in the number of acute-infected patients through the usage of the proposed method.
25	Campisi [30]	2008	Oral candidiasis	ANFIS	To evaluate the risk factors associated with oral candidiasis by means of fuzzy logic.	Predisposing factors for oral candidiasis.	Oral candidiasis	A proposed approach for the definition of the OC risk factors in an accurate way.
26	Uncu [76]	2010	COPD	FES	Conceive an FES diagnosis method for COPD diagnosi.	FEV1, FVC level.	Unstipulated	The outcome of the research has shown that using fuzzy logic could be helpful for classifying FVC graphs with great accuracy.
27	Oluwagbemi et al. [77]	2016	Ebola	FES	To develop a fuzzy system for Ebola diagnosis.	Bleeding Eyes; Bloody cough; Bleeding gums; Bleeding mouth; Backache; Breathing difficulty; Chest Pain; Fever; Fatigue; Living or visiting any Ebola-affected country in the last 3 months	Degree of the possibility of having Ebola	The FES model has the potential for using the tool as a means for predicting patient diagnosis.
28	De Moraes Lopes et al. [77]	2009	Urinary infection	Fuzzy set theory	To Develop a model to predict UI diagnosis	Urge UI, functional UI, total UI, and urinary retention, stress UI, reflex UI.	Diagnosing UI.	This system is designed to handle the fuzzy relationships with 79% accuracy.
29	Shariati [31]	2010	Hepatitis	ANFIS	To design a system to recognize the type and phase of hepatitis with ANFIS method.	Not specified.	Diagnosis of diseases	Results demonstrate that the accuracy of hepatitis and liver diagnosis was notably enhanced.
30	John [12]	2005	Influenza	Fuzzy cognitive maps	Applying the fuzzy methods to the diagnosis of Influenza.	Fever, cough, headache, muscle pains, collapse, running eyes, running nose, vertigo, chills, back pains and sore throat.	Diagnosis of disease	To Estimate the diagnosis of an Influenza diseases with great accuracy.

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
31	Uzoka et al. [78]	2011	Malaria	Fuzzy AHP	To compare the fuzzy model with the AHP method to determine malaria	A cough, loss of appetite, nausea, vomiting, fever, rigours, pain, sweating, tiredness, abdominal pain, and diarrhea.	Diagnosis of Malaria	Fuzzy logic is considered as an influential tool for malaria diagnose.
32	Sloot [79]	2005	HIV	Rule-based fuzzy logic	Multivariate analyses combined with a rule-based fuzzy logic to determine the ranking of a patient-specific drugs in HIV patients.	Data divided into four main categories: Micro Parameter, Primary Parameter, Macro Parameter, and Intervention Parameter.	Patient-specific drugs in HIV treatment	AI is efficiently used for the treatment of a drug-resistant HIV patients.
33	Mithra [80]	2018	Tuberculosis	GFNN: Gaussian-Fuzzy-Neural network	Proposing Gaussian-Fuzzy-Neural network (GFNN) for a Tuberculosis detection.	Sputum smear microscopic image database segmentation.	Bacilli count	This proposed model has achieved a better performance with the Bacilli count.
34	Hossain [81]	2017	Tuberculosis	Fuzzy Rule-Based Expert System (FRBES)	The applications of the Belief Rule-Based Expert System (BRBES) to diagnose TB.	Coughing, Coughing up blood, Fatigue, Prolonged fever, Night sweating.	Risk of tuberculosis	The generated results are more reliable for the prediction of TB in patients.
35	Langarizadeh [82]	2014	Meningitis	Rule-based fuzzy logic	This system is used to distinguish between bacterial and aseptic meningitis, by using fuzzy logic.	Gram stain, White blood cell (WBC) count in cerebrospinal fluid (CSF), Percentage of polymorphonucleocytes in CSF, CSF protein, CSF/serum glucose ratio, WBC count in blood, percentage of blood neutrophils, Blood C-reactive protein (CRP), and platelet (Plt) count.	Bacterial and aseptic meningitis	This suggested system has shown great efficiency in regards to its ability to differentiating between the bacterial and aseptic meningitis.
36	Omisore [83]	2017	Tuberculosis	Genetic-Neuro-Fuzzy	Proposing a Genetic-Neuro-Fuzzy for the diagnosis of Tuberculosis.	Swollen lymph nodes, Blood pressure, Rale breathe Abnormal breast sounds, Loss of appetite, Confusion, Cough, Fever, Chest pain, Weight loss, Night sweat, Fatigue.	Tuberculosis Diagnosis	This proposed method's sensitivity and accuracy results were 60% and 70% respectively.
37	Semogan [35]	2011	Tuberculosis	Rule-based fuzzy logic	To develop a rule-based fuzzy logic model system for Tuberculosis diagnosis.	Cough, Cough duration, body temperature, Fever duration, sputum discoloration, Nose sputum, Afternoon chills, Night sweats, Weight loss, And loss of appetite.	Tuberculosis diagnosis	A proposed CDSS integrated with Fuzzy Logic and Rule-based method produces classes of tuberculosis assessment.

Table A1 (Continued)

No.	Author	Year	Disease	Fuzzy technique	Research objective	Inward	Outward	Main conclusion
38	Uzoka [78]	2011	Malaria	Fuzzy-Analytic Hierarchy (AHP) process	A comparison between the fuzzy and AHP methods in a diagnosis system to analysis Malaria symptoms.	Fever, Rigours, Aches, Sweating, tiredness, Abdominal pain, Diarrhea, Loss of appetite, Nausea, Cough, As well as vomiting.	Malaria diagnosis	Study results have shown the superiority of the fuzzy technology over the AHP method in Malaria diagnosis.
39	Elpiniki [84]	2012	Pulmonary Infections	Fuzzy Cognitive Maps	An application of the Fuzzy Cognitive Maps for the Prediction of Pulmonary Infections.	Temperature, Systolic blood pressure, Diastolic blood pressure, Heart rate, pH, pO2, p CO2, HCO3, HCT, s O2, NA, K, WBC.	Pulmonary Infections	Results have showed less errors level in the diagnosis of pulmonary infection.
40	Mago [85]	2012	Meningitis	Fuzzy Cognitive Maps	The application of a Fuzzy cognitive map to the diagnosis of meningitis.	Sex, Cellulitis/infective focus, Immunocompromised child, Splenectomy, Bulging fontanel, Brudzinski's sign, Fever, Vomiting, Black race, Irritability, Seizures, Stiff neck, Photophobia, Head trauma, CSF study abnormal, Kernig sign, High economic/hygienic status, Hib/Pneumococcal vaccine, Good nutritional status, Possibility of Meningitis.	Meningitis diagnosis	The study has proposed FCMs for determining the symptoms and causes for meningitis patients.

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