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A fuzzy mobile decision support system for diagnosing of the angiographic status of heart disease

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Abstract

In estimating the risk of heart disease due to non-deterministic risk factors, often diagnosis of angiographic disease is difficult for physicians. For modeling and application of this uncertain and imprecise modality, decision support systems based on fuzzy logic are appropriate and an effective approach. Smartphone-based applications can facilitate the efficient use of these systems in form of evidence-based medicine. The aim of this applied study was developing and evaluating an application to diagnose angiographic disease conditions and the severity of heart attacks through a smartphone-based clinical decision support system. Android application development environment was utilized after extraction of linguistic rules and definition of membership functions needed for decisions. A smartphone-based application was designed using these guidelines and utilizing fuzzy modeling. Then, the app was evaluated in terms of accuracy using the popular Cleveland dataset. According to the results, 10 fuzzy rules for modeling, seven input variables and one decision variable were extracted. Programming was done in Eclipse. The evaluation results indicate that the accuracy of the program was 94%. Decision support systems within the context of mobile health have become some of the most efficient and influential information technology tools in recent years. They can improve patient-care management, provide easier access to the information needed for healthcare decisions and ultimately reduce healthcare costs while improving its quality.

Keywords: Smartphone, Fuzzy, CDSS, Angiography, Mobile-health, Expert system

1. Introduction

Coronary artery disease (CAD) is the most common type of heart disease. This disease is the main cause of mortality among both men and women in the United States and a leading cause of mortality, morbidity and disability with high healthcare costs in Iran. This condition occurs when the heart muscle and blood vessels become hardened and narrowed. It eventually causes chest pain (angina) and heart attack [1- 2]. Heart attack has various symptoms such as shoulder pain, chest pain, mild headache and unusual fatigue. However, some people have a heart attack without symptoms. This condition occurs more often in people who have risk factors [3]. This type of attack has greater risk than other heart attacks [4]. Since there are non-deterministic risk factors in estimating the risk of heart disease, heart disease diagnosis sometimes is difficult for professionals. In other words, there are no clear boundaries between health and disease, so diagnosis is ambiguous and may be invalid [5]. Professionals need an instrument to extract definite results from uncertain terms [6]. Managing this uncertainty is one of the most important issues for the design of decision support systems, because a lot of available information in a knowledge base is imprecise [7].

Fuzzy logic is an expanded method of traditional logic systems. It is also a conceptual framework for knowledge representation in imprecise environments [8]. Given the complexity of medicine, that makes old quantitative methods inappropriate in analysis due to a lack of information or poor accuracy. In many cases, contradictory information is presented. This method is an appropriate approach for the design of medical decision support systems [9]. Mobile and smartphones have quickly become the primary communication tool between individuals. These phones have the potential to be programmed for many additional features [10-11]. The use of information and communications technology (ICT), especially mobile applications in e-health is a promising way to improve user-friendliness and therefore, increase the effectiveness of actions such as assessment. Mobile phones have the benefit of providing continuous and timely access to information [12]. Development of applications for smartphones and tablets has attracted attention in many fields. In healthcare, new application domains such as clinical decision support systems (CDSS), Home Tele-monitoring or help at home, based on portable devices are expanding [13-15]. CDSS is defined as software that is designed to be a direct aid to clinical decision-making, in which the characteristics of a

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Table 1 The features used in this study for decision-making

Variable type	Variable name	Linguistic values	Numerical values
Input	Chest pain type	Typical angina	1
		Atypical angina	2
		Non typical-angina	3
		Asymptomatic angina	4
	Resting blood pressure	Min	110<rbp<145
		Max	145<= rbp
	Serum cholesterol	Min level	168<=chol<=240
		Max level	chol>240
	Number of years smoking	Low possibility	Age<=30
		High possibility	Age>30
	Fasting blood sugar	Sugar level= no	Fbs<=120
		Sugar level = yes	Fbs>120
	Maximum heart rate achieved	Min_heart_rate	50<=bpr<=70
		Max_heart_rate	Bpr>70
	Resting blood rate achieved	low_blood_rate	90<=rbr<=140
		high_blood_rate	rbr>140
Output	Angiographic disease status	Mild	0 - < 50% diameter narrowing
		Massive	1- > 50% diameter narrowing

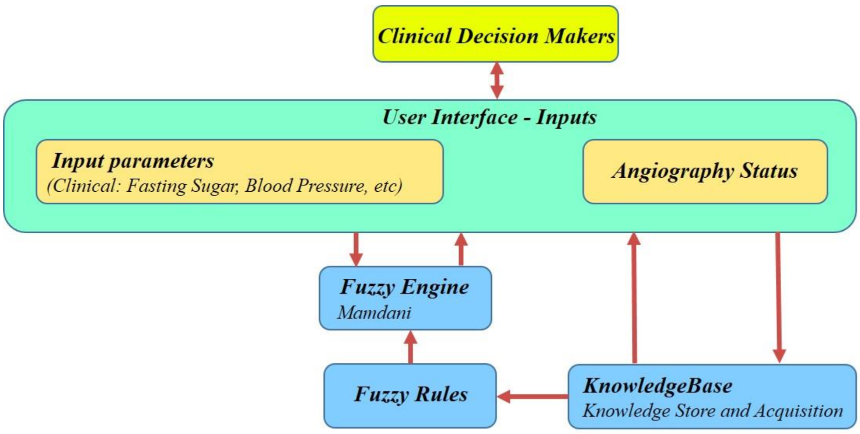

Figure 1 The architecture of fuzzy clinical decision support system

patient are matched to a knowledge base and recommendations are then presented to the physician. Mobile applications are cost-effective and highly available tools to implement monitoring and management in healthcare, especially in CDSS development.

This technology benefits computers with the power of a network, and covers a wide range of health domains [16]. The current study aims to indicate the extent and severity of heart attack by performing disease diagnosis and indicating the severity of a heart attack through a clinical decision support system based on smartphones. It will use the angiographic condition of patients with heart disease, which is represented by a numerical value between 0 and 1. In the study, previous research data were used. In fact, the desired task is to classify variables derived from the Cleveland heart disease dataset. Using previous laboratory studies, this study intends to take advantage of the methods and results of earlier studies. Due to the increasing proliferation of smartphone applications, a mobile fuzzy system will provide a diagnosis of heart disease using quick access to the tools of artificial intelligence at the point of care.

2. Materials and methods

2.1 Dataset

In this study, the Cleveland heart disease dataset was used. This dataset is part of a University of California database collected by David Aha. This dataset consists of diagnoses of the presence or absence of heart disease, according to tests done on patients. It consists of 76 variables and 303 data records. Even so, most studies using this dataset used only 14 important variables. Eight variables were selected in the current study that were used in previous studies on feature selection methods [17-20]. Seven input variables and one output variable (shown in Table 1) were used to create decision rules. These variables include the type of chest pain, four types of common pain, blood pressure at rest (in mm Hg), serum cholesterol (in mg), and number of years of smoking, blood sugar, heart rate, maximum heart rate and maximum blood pressure at rest. A coronary angiography condition is considered as an output that indicates the severity of a heart attack on two scales, mild and massive. The ranges of values for these variables are listed in the Table 1.

2.2 Fuzzy modeling

A fuzzy decision support system is comprised of four components, a fuzzification module, knowledge base, decision logic module, and defuzzification module, all of which should be embedded in the architecture details. An overview of this system architecture is shown in Figure 1.

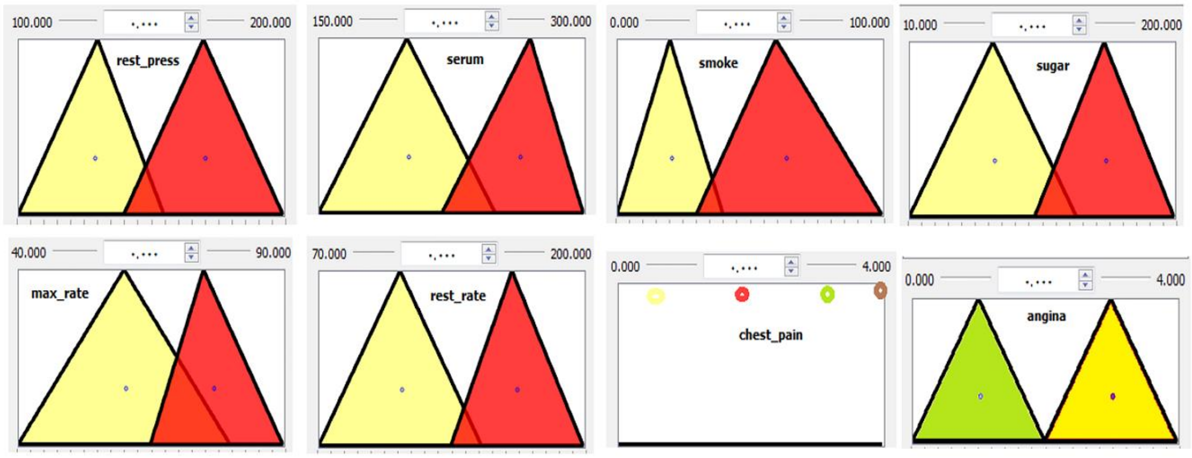

Figure 2 The membership functions of affective variables in cardiac diagnosis, the modeling was performed using qtfuzzylite

Fuzzy membership functions were used for modeling the issue variables. These functions determine the values of membership of objects in a fuzzy variable set. There are various forms of membership functions. The most basic form of membership function is a triangular. In a triangular membership function, if p, q and r are three coordinates of X, μA (x) Y coordinates show in an "A" fuzzy set. If the "p" is a lower bound and "r" an upper bound where the membership degree is equal to zero and "q" is the center of the place which degree of membership is equal 1 [21], Equation (1) is as follows:

Fuzzy membership function:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \le p \\ \dfrac{x-p}{q-p} & \text{if } p \le x \le q \\ \dfrac{r-x}{r-q} & \text{if } q \le x \le r \\ 0 & \text{if } x \ge r \end{cases} \quad (1)$$

Fuzzy Lite was used as a control library of Fuzzy logic for development and coding the fuzzy model in the smartphone application development environment. This is a platform-independent, free and open source application that is written in C++. The purpose of this library is to prepare, design and operate fuzzy logic controllers with an object-oriented approach. This library has features for various controllers, mathematical calculations and various methods for defuzzification. It can be used in Java and Android programming environments such as Eclipse [22]. Earlier studies were reviewed and evaluated to determine the accuracy of the system. A purposeful search was conducted using search engines and databases such as Google scholar, PubMed and IEEE and ACM. The inclusion criteria were publication date (before Aug 2019) and a direct connection with the data. Exclusion criteria were defuzzification and nonsystematic methods. The Cleveland AND UCI AND Heart AND Fuzzy AND Intelligent keywords were used to search. From 1503 records returned, 22 of the most relevant papers were included.

We used Equation (2) to evaluate accuracy. It is a standard formula for diagnostic tests, which was introduced as the main outcome of a CDSS. This formula applied by all the reviewed studies to express accuracy:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (2)$$

3. Results

According to the extracted information from previous studies using the Cleveland heart disease dataset and triangular membership functions, the fuzzy inputs and outputs were modeled with "qtfuzzylite" as depicted in Figure 2. Additionally, a sample user interface of the application is displayed in Figure 3.

Fuzzy rules were extracted using research papers and clinical guidelines as in Table 2. These rules were stored in a coronary angiography rule base to evaluate the condition of patients. They were implemented in the Java programming language using the Fuzzy Lite Library. The Mamdani inference model was used for defuzzification computing using the center of area (centroid) method.

In Table 2, the fuzzy rules to diagnose cardiovascular disease (angina condition or severe heart attack) based upon the input membership functions are presented.

4. Discussion

Evidence-based practice and evidence at the bedside are key issues in modern medicine. A prime barrier is time. Decision support systems can quickly take advantage of evidence and guidelines [22]. Mobile decision support systems that incorporate this technology in handheld computers and smartphones could aid in providing proper care to patients [14, 23]. Clinical decision support systems are computer systems that are designed to improve clinical decision making. If clinical decision support systems are used correctly, they have the potential to change learned and operational medical practices [24].

Therefore, perception of usefulness of these systems to help in the diagnosis of heart disease is very important. The designed decision support system in this study, according to an evidence-based approach and applying related guidelines, can increase the accuracy of diagnosis of the severity of cardiac disease and lead to reduced diagnostic error. Alternatively, due to high availability of these systems through smartphones, their use will increase. This will promote further the use of clinical evidence. Fuzzy logic is used to describe and explain imprecise as well as uncertain

Table 2 Fuzzy rules to diagnose angiographic status

No.	Fuzzy rules
1	if chestpain is ASYMPTOMATIC and restpress is MN and serum is MAXLEVEL and smoke is LOWPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is HIGHRATE then angin is MASSIVE
2	if chestpain is NONANGIN and restpress is MN and serum is MAXLEVEL and smoke is HIGHPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is HIGHRATE then angin is MILD
3	if chestpain is ATYPIC and restpress is MN and serum is MAXLEVEL and smoke is LOWPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is HIGHRATE then angin is MILD
4	if chestpain is ATYPIC and restpress is MN and serum is MAXLEVEL and smoke is HIGHPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is LOWRATE then angin is MILD
5	if chestpain is ASYMPTOMATIC and restpress is MAX and serum is MINLEVEL and smoke is LOWPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is LOWRATE then angin is MILD
6	if chestpain is ASYMPTOMATIC and restpress is MAX and serum is MAXLEVEL and smoke is LOWPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is HIGHRATE then angin is MASSIVE
7	if chestpain is ASYMPTOMATIC and restpress is MAX and serum is MAXLEVEL and smoke is HIGHPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is LOWRATE then angin is MILD
8	if chestpain is ATYPIC and restpress is MN and serum is MAXLEVEL and smoke is HIGHPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is LOWRATE then angin is MILD
9	if chestpain is NONANGINE and restpress is MN and serum is MAXLEVEL and smoke is HIGHPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is LOWRATE then angin is MILD
10	if chestpain is ASYMPTOMATIC and restpress is MAX and serum is MAXLEVEL and smoke is LOWPOSSIBILITY and sugar is LEVENO and maxrate is MNRATE and restrate is HIGHRATE then angin is MASSIVE

Figure 3 Mobile phone-based decision support system user interface for diagnosis of heart disease

concepts. Medical decision making is an area of uncertainty [25].

The use of fuzzy logic to handle complex issues such as decision-making and medical diagnosis leads to modeling uncertainties [26]. In this study, clinical guidelines have many ambiguous concepts, especially in the diagnosis and determination of disease severity. The proposed system was designed as a decision model using fuzzy logic and employs the practices of decision support systems. The designed clinical decision support system was evaluated using 303 heart disease records. In the current study, a fuzzy classifier was employed as a diagnostic tool and severity of heart attack analysis was conducted examining the characteristics of people with heart disease.

As is clear from the results presented in Table 3, approximately a 94% classifier accuracy was achieved, which meets the appropriate knowledge and system engineering standards (TP: 163 , TN: 123, FP:7 , FN:10). According to the performance results obtained, fuzzy set specifications and features should be designed, specifically, to do diagnosis in the shortest possible time, with minimal error. Therefore, they can be used to speed up diagnosis and, more importantly, be used in any place without physician assistance.

Previous studies using the Cleveland heart dataset from 2010 to 2016 were employed as system evaluation criterion. These results are shown in Table 3. The highest accuracy was achieved by a neural network, and considering the ambiguity in the method. However, it produced unreliable results. Other results ranged from 75 to 97% accuracy, which are considered acceptable. Even so, the strength of the system is not its high precision. Rather, it provides a mobile application that is exclusively in the hands of physicians at all hours and under all conditions, with improved access in the simplest form possible. Today iPhone and Android-based systems are two preferred platforms. Competition between the two operating systems has improved their power. Android mobile operating systems are open source operating systems that have the capability to run on a wide range of handsets. Application developers will also be able to create applications for them. Therefore, the capabilities of open-source programming is an important feature in the development of android apps [27]. This approach can lead pervasive decision support systems in health communities. Android apps use of the capabilities of the Java language without compromising quality. Java integrated development environments, such as Eclipse, can be used for development [28].

Pervasive decision support systems are now possible in mobile health and health social media [48]. Previous fuzzy models using the selected dataset focused on the computational aspects of the problem space. Some reached 100% accuracy on scientific toolboxes such as Matlab.

Table 3 Comparison of similar studies on the same heart dataset and reported accuracies

Paper	Method	Accuracy %	Year
Abushariah MAM, et al. [29]	ANFIS	75.93	2014
	ANN	87.04	
Krishnaiah V, et al. [30]	Adapting rough–fuzzy classifier	81	2014
Thanh Nguyen et al. [31]	GSAM combined wavelet transformation	78.78	2015
Hedeshi NG et al. [32]	fuzzy-boosting PSO	85.76	2014
Hamza Turabieh[33]	Hybrid ANN-GWO	73.43	2016
Dennis B et al. [34]	Adaptive Genetic Fuzzy System	76	2014
Nahato et al. [35]	Hybrid fuzzy sets and extreme learning machine	93.55	2016
Long NC , et al. [36]	firefly based	88.3	2015
Ziasabounchi and Askerzade[37]	ANFIS	92.30	2014
Samuel OW [38]	Fuzzy AHP, ANN	91.10	2017
Ali. Adeli, Mehdi. Neshat [9]	Fuzzy logic	94	2010
Vahid Khatibi, Gholam Ali Montazer [39]	fuzzy-evidential hybrid inference engine	91/58	2010
Anooj P.K [40]	Weighted fuzzy rules	57/85	2011
Vanisree K and Jyothi Singaraju [41]	Neural network	90	2011
Barman M, Choudhury JP [17]	ANFIS	90	2012
Dangare CS et al. [42]	Neural network, data mining	100	2012
Anooj P K et al. [43]	Fuzzy evidential system	88.09	2019
Kaan U, İlhan A [44]	recurrent fuzzy neural network	97.78	2017
Animesh Kumar Paul et al. [45]	weighted fuzzy rule	92.31	2018
Reddy GT, Khare N [46]	oppositional firefly with BAT and rule-based fuzzy logic (RBFL)	78	2017
Oumaima Terrada et al. [47]	Fuzzy	100	2018
Current Study	Fuzzy rules guideline based	94	2019

Unfortunately, none of these studies contain user experience capabilities. Using mobile health concepts and approaches, our study product is an operational application for future studies examining usability and user experience. Nowadays, without real-world applications in health and biomedicine, accuracy and other computational measures are not efficient. Recent studies emphasized usability and user satisfaction as important features of a CDSS [49-51]. In comparison to other studies, the framework of this study has more potential in actual biomedical applications.

5. Conclusions

According to studies, decision support systems within the context of mobile health are one of the most efficient and influential information technology tools in recent years. They can improve patient-care management, provide easier access to the information needed for health and ultimately reduce healthcare costs and improve quality. In general, it can be claimed that studies on the use of such CDSS in finding medical diagnosis are very promising for the future. This study also aims to determine the severity of a heart attack and has taken a step towards a more complete and precise diagnosis. The product is usable by a healthcare team and in self-care for heart patients. Also, knowledge-based fuzzy expert systems are suitable instruments to model clinical guideline evidence in a rule-based manner. The outcome of this paper is a portable accurate knowledge-based CDSS in a cardiovascular specialty that will remove accessibility obstacles. It will do so by using healthcare expert systems through proper design and development technologies, environments, and tools. The use of computational methods and development of network-based systems is recommended. This will provide a possibility of receiving a more accurate diagnosis and expand the use of mobile health systems, in particular, clinical decision supports systems.

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