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ORIGINAL PAPER

Developing a Fuzzy Expert System to Predict the Risk of Neonatal Death

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ABSTRACT

Introduction: This study aims at developing a fuzzy expert system to predict the possibility of neonatal death. **Materials and Methods**: A questionnaire was given to Iranian neonatologists and the more important factors were identified based on their answers. Then, a computing model was designed considering the fuzziness of variables having the highest neonatal mortality risk. The inference engine used was Mamdani's method and the output was the risk of neonatal death given as a percentage. To validate the designed system, neonates' medical records real data at a Tehran hospital were used. MATLAB software was applied to build the model, and user interface was developed by C# programming in Visual Studio platform as bilingual (English and Farsi user interface). **Results:** According to the results, the accuracy, sensitivity, and specificity of the model were 90%, 83% and 97%, respectively. **Conclusion:** The designed fuzzy expert system for neonatal death prediction showed good accuracy as well as proper specificity, and could be utilized in general hospitals as a clinical decision support tool.

Key words: Expert systems, fuzzy logic, perinatal death, decision support system, clinical.

1. INTRODUCTION

The first 28 days after birth is referred to as neonatal period and is considered as a vulnerable time for neonates. Meanwhile, the mortality rate of newborns in the first 24 hours of life is the highest and includes 65% of deaths under one year (1). According to the results released by UNICEF, almost 1 million newborn babies died on the first day of life in 2013, that is, 36% of all infant deaths. Besides, in total, 2 million newborn babies died in the first 7 days after birth; in other words, 73% of neonatal deaths occur in this period. In fact, between 1990 and 2013, 86 million newborns died during the first 28 days of life (2). According to the World Bank's definition, neonatal mortality rate is the number of neonates per 1000 live birth in a given year, that die before reaching 28 days of age (3). Based on the reports published by UNICEF, neonatal mortality rate is 10.3 per 1000 live births in Iran in 2015 (4), and based on WHO recommendations, interventions aimed to decrease neonatal mortality rate must be done (5). Being aware of the main causes of perinatal mortality and factors affecting them plays an important role in planning to improve a suitable system for perinatal care, delivery and newborns (6).

Meanwhile, different clinical decision support systems are implemented based on artificial intelligence and are increasingly used in hospitals and clinics (7). Uncertainty, vagueness, and imprecision are very common in medicine. Fuzzy set theory has been developed to deal with the concept of partial true values ranging from completely true to completely false, and has become a powerful tool for dealing with imprecision and uncertainty (8, 9). The prediction of neonatal death can support critical information for intensive care specialists according to newborn condition. It is obvious that in small hospitals and poor medical facilities, lack of access to appropriate clinical staff and proper instruments leads to newborns' death. Therefore, developing an expert system based on fuzzy logic can be helpful in reducing neonatal mortality.

In (8), a fuzzy linguistic model was made based on birth weight and gestational age by using Mamdani inference. In (9), a fuzzy predictive model was developed for establishing the risk of neonatal death based on the fuzziness of the following variables: birth weight, gestational age, Apgar score, and previous stillbirth. Madmani inference was used and the output was the risk of neonatal death given as a percentage. In (10), a fuzzy inference system was developed to create a knowledge base for the diagnosis and detection of sepsis using MATLAB fuzzy logic toolbox. In (11), fuzzy expert system was applied to advanced neonatal resuscitation efforts in the delivery room. The fuzzy expert system presented a sensitivity of 76.5% and a specificity of 94.8% in the identification of the need for advanced neonatal resuscitation measures. In (12), fuzzy theory was applied to the Apgar Scoring System (APG) to design an Apgar Fuzzy Expert System (AFES). Statistical analysis was done on the outcome and showed that AFES, as determined by expert neonatologists, had the highest sensitivity compared with different forms of APG.

2. MATERIALS AND METHODS

2.1. Definition of risk factors

A list of important criteria having an overall risk to the newborn was found in medical literature. Neonatal scoring systems such as SNAP, CRIB and SNAP-PE were reviewed by the researchers and a neonatologist. A set of critical risk factors was organized in a questionnaire and was completed by a neonatologist in educational children's hospitals of Tehran University of Medical Science, Iran University of Medical Science, and Shahid Beheshti University of Medical Science. According to the completed questionnaires, 16 out of 46 weighted parameters having the highest effect on neonatal death were selected based on the attitude of X neonatologists. A list of risk factors is shown in Table 1.

No.	Risk factor for neonatal death	No.	Risk factor for neonatal death
1	Birth Weight	8	Malformation
2	Gestational Age	9	PaO2[1]
3	Apgar Score	10	PaCO2[2]
4	Neonate's Status in Delivery	11	Serum pH
5	Mother's Age	12	Respiration Rate
6	Previous Multiple	13	Base Excess
7	Diabetic Mother	14	Previous Stillbirth

Table 1. Weighted risk factors affecting neonatal death according to Iranian neonatologist attitudes

2.2. Fuzzy Expert System

A computational model is used with a fuzzy model based on Mamdani inference system to predict the risk of neonatal death. A fuzzy linguistic model is a rule-based system that uses the fuzzy set theory to address the issues. Its base structure includes four main components:

- A fuzzifier, which translates crisp input (classical numbers) into fuzzy values;
- An inference engine, that applies a fuzzy reasoning mechanism to obtain a fuzzy output (in the case of Mamdani inference);
- A knowledge base, which contains both a set of fuzzy rules and a set of membership functions representing the fuzzy sets of linguistic variables, and
- A defuzzifier, which translates the fuzzy output into crisp values.

The decision process is performed by the inference engine using values contained in the rule base. These fuzzy rules define the connection between fuzzy input and output. A fuzzy rule has a form: if antecedent, then consequent, where the antecedent is expressed by fuzzy operators and the consequent is an expression that assigns fuzzy values to the output variables. The inference process evaluates all rules in the rule base and combines the weighted consequence of all relevant rules into a single output fuzzy set (Mamdani model). The fuzzy output set may then be replaced by a "crisp" output value obtained by a process called defuzzification (8, 13).

The detailed description of input variables, fuzzy set variables, and membership functions is shown in Table 2. It is to be mentioned that in order to reach the best outcome, normalization of variables was done in interval -1 to +1 using the related formula in MATLAB software because the range of variable was varied.

Since there were a lot of input variables in this study, combining all possible inputs leads to the construction of so many rules. However, in order to increase efficiency and reduce complexity, just relevant rules were considered based on neonatologist opinion. Sum was the aggregation method used in this research; meanwhile, in order to defuzzify, centroid method was applied and the risk of neonatal death was predicted as a percentage. MATLAB software 2012 was used

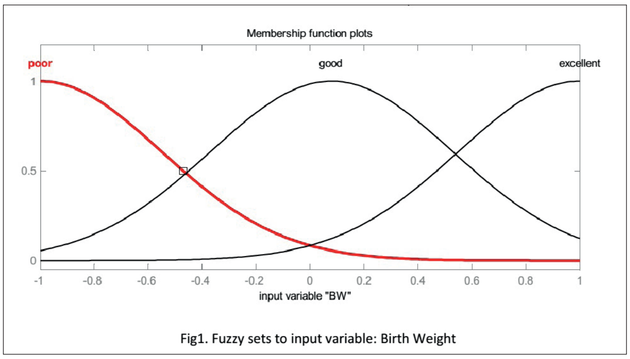

Figure 1. Fuzzy sets to input variables: Birth Weight

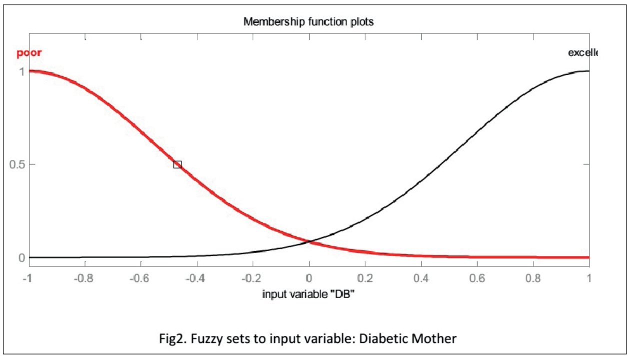

Figure 2. Fuzzy sets to input variables: Diabetic Mother

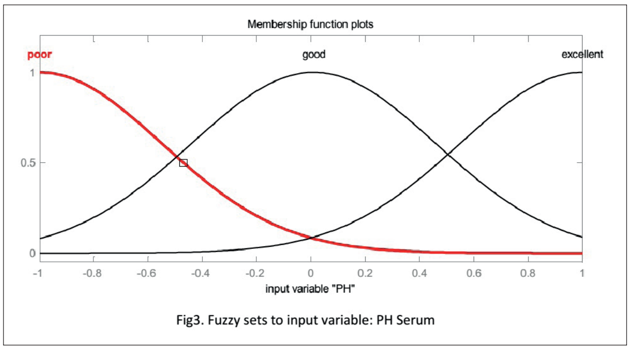

Figure 3. Fuzzy sets to input variables: PH serum

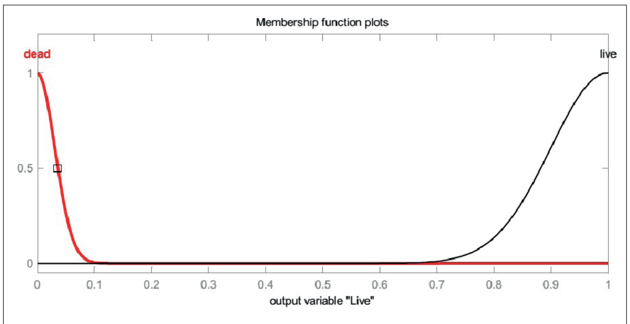

Fig4. Fuzzy sets to output variable: Risk of neonatal death

Figure 4. Fuzzy sets to output variables: Risk of neonatal death

to build the model and to increase the efficiency and user-friendliness of the system; user interface was designed by Visual Studio and C# programming language in bi-lingual form (Persian and English).

2.3. Experimental Analysis

To evaluate the performance of the developed fuzzy expert system, a list of medical records of neonates, hospitalized in NICU and high-risk center of Moheb Yas Women's General Hospital in Tehran from March to December 2014, was reviewed. The collected cases were then analyzed to compare the outcome of the system and the results in medical records. After that, the accuracy, specificity, and sensitivity of the predictive model were determined based on the analyzed data.

3. RESULTS

3.1. Membership functions and fuzzy production rules

The fuzzy sets related to some of the linguistic input variables are presented in Figures 1 to 3. Membership degree indicates that the input belongs to the set. Figure 4 shows the membership function of the output variable "risk of neonatal death". Figure 4 corresponds to the representation of graphic user interface of system that designed bilingual (Farsi and English).

In order to validate the predictive fuzzy system, the neonates' medical records were reviewed to compare the results in the real data set with those in the fuzzy predictive system for neonatal death. Accuracy, specificity, and sensitivity indicators were calculated and the figures turned out to be 90%, 97% and 83%, respectively.

4. DISCUSSION

The developed fuzzy expert system was evaluated with the real data of neonates' medical records to measure performance and its effectiveness, and the results were acceptable. Considering the fact that the most important part of knowledge-based fuzzy inference system is the knowledge base that makes the inference engine, the present researchers applied the knowledge of experts (neonatologists); that is, they converted them to fuzzy rules (IF-THEN rules) and used them in the inference engine. The study showed that Fuzzy Inference System (FIS) works by transforming qual-

Figure 5. Farsi Graphic User Interface of neonatal death predictive system

No.	Variable		Variable Value	Actual Range of Variable	Fuzzy Range after Normalization	Membership Function
1	Input	Birth Weight	Very Low Birth Weight	<1500	-1 to +1	Guassmf
			Low Birth Weight	<2500	-1 to +1	Guassmf
			Normal Birth Weight	>2500	-1 to +1	Guassmf
2		Gestational Age	Pre-term	<37	-1 to +1	Guassmf
			Term	37-42	-1 to +1	Guassmf
			Post-term	>42	-1 to +1	Guassmf
3		Apgar Score	Low	0-4	-1 to +1	Guassmf
			Normal	4-8	-1 to +1	Guassmf
			High	8-10	-1 to +1	Guassmf
4		Neonate's Status in Delivery	Negative	0	-1 to +1	Guassmf
			Positive	1	-1 to +1	Guassmf
5		Mother's Age	Low	<18	-1 to +1	Guassmf
			Normal	18-35	-1 to +1	Guassmf
			High	>35	-1 to +1	Guassmf
6		Previous Multiple	Negative	0	-1 to +1	Guassmf
			Positive	1	-1 to +1	Guassmf
7		Diabetic Mother	Negative	0	-1 to +1	Guassmf
			Positive	1	-1 to +1	Guassmf
8		Malformation	Negative	0	-1 to +1	Guassmf
			Positive	1	-1 to +1	Guassmf
9		PaO2	Low	<45	-1 to +1	Guassmf
			Normal	45-65	-1 to +1	Guassmf
			High	>65	-1 to +1	Guassmf
10		PaCo2	Low	<50	-1 to +1	Guassmf
			Normal	50-65	-1 to +1	Guassmf
			High	>65	-1 to +1	Guassmf
11		Serum pH	Low	<7	-1 to +1	Guassmf
			Normal	7.10-7.19	-1 to +1	Guassmf
			High	>=7.20	-1 to +1	Guassmf
12		Respiratory Rate	Low	<30	-1 to +1	Guassmf
			Normal	30-60	-1 to +1	Guassmf
			High	>60	-1 to +1	Guassmf
13		Base Excess	Low	<-10	-1 to +1	Guassmf
			Normal	-10 to -15	-1 to +1	Guassmf
			High	>-15	-1 to +1	Guassmf
14		Previous Stillbirth	Positive	0	-1 to +1	Guassmf
			Negative	1	-1 to +1	Guassmf
1	Output	Risk of Neonatal Death	Neonatal death	1	-1 to +1	Guassmf
			Neonatal life	0	-1 to +1	Guassmf

Table 2. Variable, actual range, fuzzy range and membership function

itative data of neonates and their mothers' health status to numeric values that make it possible to quantify the risk of neonatal death. To validate the designed system, the present researchers evaluated the outcome of the predictive system using real data from neonates' medical records. The KB-FIS revealed good outcome and generated rules for decision support. According to neonatologists' opinions, the selection of critical risk factors in neonatal death was considered as a positive point in this study because the proper selection of important variables leads to the right output in the designed system. In similar studies conducted on the prediction of neonatal death risk (8, 9), researchers achieved results which are comparable with those of the present study. In (9), Spearman's correlation coefficient was used for the comparison of model results and the experts' opinions. In (8), accuracy is equal to that of the present study (90%), but sensitivity in the present research is 83% and is more than that of the mentioned study (70%), which can be a good point in the present study to compare with related researches.

5. CONCLUSION

The fuzzy expert system can be used as a teaching tool that can help NICU nurses or inexperienced clinicians and medical students to predict and identify emergency situations. It can be added that the presence of this kind of clinical decision support system can help decision makers in perinatal care in situations where skilled specialists and advanced equipment are not available. It is important to bear in mind that the fuzzy expert system and, broadly speaking, the clinical decision support system must be employed along with clinicians, and should not replace them.

- **Author's contribution:** All authors were fully involved in the study and preparation of the manuscript including: the conception and design of the study, acquisition of data, analysis and interpretation of data, drafting or revising the article.
- **Conflict of interest:** none declared.

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