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Fuzzy linguistic model for evaluating the risk of neonatal death

Modelo lingüístico fuzzy para estimação do risco de morte neonatal

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Keywords
Neonatal mortality (public health). Fuzzy logic. Risk factors. Birth weight. Gestational age. Neonatal death.

Abstract

Objective
To introduce a fuzzy linguistic model for evaluating the risk of neonatal death.
Methods
The study is based on the fuzziness of the variables newborn birth weight and gestational age at delivery. The inference used was Mamdani's method. Neonatologists were interviewed to estimate the risk of neonatal death under certain conditions and to allow comparing their opinions and the model values.
Results
The results were compared with experts' opinions and the Fuzzy model was able to capture the expert knowledge with a strong correlation (r=0.96).
Conclusions
The linguistic model was able to estimate the risk of neonatal death when compared to experts' performance.

Descritores
Mortalidade neonatal (saúde pública). Lógica fuzzy. Fatores de risco. Peso ao nascer. Idade gestacional. Mortalidade neonatal.

Resumo

Objetivo
Apresentar um modelo linguístico fuzzy *para estimar o risco de morte neonatal.*
Métodos
Baseia-se nas variáveis peso ao nascer e idade gestacional, consideradas como variáveis fuzificadas; a inferência utilizada foi o método de Mamdani; foram entrevistados neonatologistas para estimar o risco de morte neonatal sob determinadas condições de peso e idade gestacional e compararam-se estes valores com aqueles estimados pelo modelo.
Resultados
Os resultados do modelo apresentam boa correlação com os valores atribuídos pelos especialistas com r=0,96.
Conclusões
O modelo lingüístico fuzzy *proposto apresentou boa concordância quando comparado com as estimativas dos especialistas, para os valores de risco de morte neonatal.*

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INTRODUCTION

In bioscience there are several levels of uncertainty, vagueness, and imprecision, particularly in the medical and epidemiological areas, where the best and most useful description of disease entities often comprise linguistic terms that are inevitably vague.

The theory of Fuzzy Logic has been developed to deal with the concept of partial truth values, ranging from *completely true* to *completely false*, and has become a powerful tool for dealing with imprecision and uncertainty aiming at tractability, robustness and low-cost solutions for real-world problems.

These features and the ability to deal with linguistic terms could explain the increasing number of works applying Fuzzy Logic in biomedicine problems.[12,14] In fact, the theory of Fuzzy Sets has become an important mathematical approach in diagnosis systems,[2] treatment of medical images[4] and, more recently, in epidemiology[6,9,15] and public health.[7]

The capability of working with linguistic variables, easiness of understanding, low computational cost, and its ability to incorporate to the systems the human expert experience, are attributes that make this approach an extremely interesting option to elaborate medical models. The basic concepts of the fuzzy sets theory is presented in the next section.

Neonatal mortality is defined as the death that occurs up to 28 days of life and it is a very important population health indicator. This indicator provides information on social welfare, and ethical and political aspects of a population under certain conditions. Among the main causes of neonatal mortality, low birth weight (LBW) preterm newborn (PT) are the most important. There is a classification for preterm and low birth weight children. Those whose are bornweighing less than 2,500 g are considered low birth weight, and among them, those who are born weighing less than 1,500 g are considered very low birth weight. Correspondingly, children who are born before having completed 37 weeks of gestation are considered preterm, and extreme pre-term are those born before having completed 32 weeks of gestation.[1]

The incidences of LBW and PT in Brazil are around 10%.[3,5] The estimate of the risk of neonatal death can provide important information to pediatricians, especially to neonatal intensive care physicians, with respect to the attention a newborn requires. Nevertheless, a possible source of confusion could be the *Boolean* classification for PT and LBW described above, because let's say an infant born weighing 2,600 g might not receive the necessary attention because this infant is not considered LBW. The same could happen with an infant born at 38 weeks of gestation. Low birth weight, extreme low birth weight, preterm and extreme pre-term newborns are the main risk factors to neonatal mortality. Neonatal mortality in the state of São Paulo, the most industrialized Brazilian state, in 2000 was 11.45/1000 livebirths.[13]

It is evident that the care provided to a newborn infant could differ depending on the hospital and its location (whether they are in more developed or more populous areas, rural or urban zone, etc.). It is common in fairly small hospitals the pediatrician is not there at the time of birth, and other professionals are in charge of evaluating the newborn.

To estimate the risk of neonatal deaths, it has been applied a Logistic Regression Model using dichotomous independent variables such as Yes or No, Present or Absent.[8] As opposed to Logistic Regression, Fuzzy Logic allows assigning, for instance, a newborn with birth weight of 1,350 g to a fuzzy subset VLBW with 0.63 membership degree and to a LBW fuzzy subset with 0.25 membership degree, bringing in the inherent uncertainties of this record. In fact, a newborn weighing 1,490 g at birth and another weighing 1,510 g at birth, who are classically categorized as LBW and IBW respectively, do not show significant differences on biological, anatomical and physiological aspects. In the fuzzy approach each element may be compatible with several categories, with different membership degrees. The advantage of the fuzzy theory is to consider an even and more realistic classification of the children relating to the two variables assumed.

Considering the scenario discussed above, the development of a simple, low cost program, which is able to evaluate more appropriately the risk of neonatal death, could become an important tool. Thus, it is presented in the study a theoretical fuzzy linguistic model to estimate the risk of neonatal death based on birth weight and gestational age.

Fuzzy sets theory

The theory of fuzzy sets was introduced by Lotfi A. Zadeh[17] from the University of California, Berkeley, in the 1960's as a means to model the uncertainty within natural language and introduced vagueness concept. Among the various paradigmatic changes in science and mathematics in the last century, one such change concerns to the concept of uncertainty. According to the traditional view, science should

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strive for certainty in all its manifestation (precision, specificity, sharpness, consistency, etc.); hence, uncertainty (imprecision, non-specificity, vagueness, inconsistency, etc.) is regarded as unscientific. According to the alternative view, uncertainty is considered essential to science.

Zadeh's key notion was graded membership, according to which a set could have members who fit into it partly. So, if one assumes X is a set serving as the universe of discourse, a *fuzzy subset A* of X is associated with a function which is generally called *membership function*. The idea is that for each x, $m_A(x)$ indicates the degree to which x is a member of the fuzzy set A. This membership degree indicates the compatibility degree of the assertion "*x is A*".

$$\mu_A : X \rightarrow [0,1]$$

The classic set theoretical operations can thus be extended to fuzzy sets, which have membership grades that are in the interval *[0,1]*. So, if one assumes that A and B are two fuzzy subsets of $\boldsymbol{X}$, their standard union, intersection, and complement are also fuzzy sets given by:

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)]$$

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)]$$

and

$$\mu_{\underline{A}}(x) = 1 - \mu_A(x)$$

where $\underline{A}$ is the negation of A (not A). Union, intersection and complement defined above are fuzzy operators that one can use to combine fuzzy variables to form fuzzy expressions, as aggregating fuzzy rules.

Sometimes, a fuzzy set could represent linguistic concepts, such as *very small*, *small*, *high, and so on*, as interpreted in a particular context, resulting in the named *linguistic variable*. It is characterized by its name tag, a set of fuzzy values (linguistic terms) and the membership functions of these labels. Consider, for example, the linguistic variable named *Fever* with a set of linguistic terms representing *absent fever*, *moderated fever* and *intense fever*. So, *Fever* is a concept that could be translated by fuzzy sets, which membership functions express quantitatively the notions of f*ever absent*, *fever moderated* and *intense fever.* The ability to operate with linguistic variable is one of the most important characteristics of fuzzy sets theory and its successful applications.

A fuzzy linguistic model is a rule-based system that uses fuzzy sets theory to treat the phenomena. Its basic structure includes four main components:

- a fuzzyfier, which translates crisp (classical numbers) inputs 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 function representing the fuzzy sets of the linguistic variable; and
- a defuzzifier, which translates the fuzzy output into a crisp value. The decision process is performed by the inference engine using the rules contained in the rule base. This fuzzy rules define the connection between fuzzy input and output. A fuzzy rule has a form:

If antecedent then consequent, where *antecedent* is a fuzzy expression composed by one or more fuzzy sets connected by fuzzy operators, and *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 consequents of all relevant rules into a single output fuzzy set (Mamdani's model). In many applications of the fuzzy theory it is necessary to produce crisp value as the result of an approximate reasoning process. The fuzzy output set may then be replaced by a "crisp" output value obtained by a process called defuzzification. There are many methods to defuzzify a fuzzy output, but in all of them the crisp value found reflects the best representation of fuzzy set defuzzified.[16]

The brief outline above describes fuzzy set theory and the approximate reasoning process in its simplest and most commonly used form. There are a variety of other approaches at different levels, perhaps most notably in the choice of the aggregation operators, and in the definition of the inference operation. To the reader who wishes to learn more about fuzzy logic theory it is recommended the book by Yen and Langari.[16]

METHODS

A linguistic fuzzy model is consists of a set of fuzzy rules and an inference method. The most common inference method is the Minimum of Mamdani, whose output is a fuzzy set. In general, Mamdani's fuzzy models are completely based on experts experience. If one is interested in a crisp output it is possible to find it with a defuzzification method, like a Center of Area.[14,15]

The fuzzy linguistic model to evaluate a risk of neonatal death has two antecedents: birth weight and gestational age. The model was developed from one expert knowledge, who elaborated four fuzzy sets to the variable birth weight: *very low birth weight* (VLBW), *low birth weight* (LBW), *insufficient birth weight* (IBW), and *normal birth weight* (N); and three fuzzy sets to the variable gestational age: *very preterm* (VPT), *preterm* (PT) and *term* (T*)*. These fuzzy sets were built with fuzzification of the classical pediatrics classification.

The consequence of the model is the *risk of death until 28 days*. The expert considered four fuzzy sets for this linguistic variable: *very low (VLR)*, *low (LR)*, a *little high (LHR)* and *high (HR)*.

The base rules consisted of the following ones:

1. IF *weight* is VLBW AND *gestational age* is VPT THEN *Risk* is HR.
2. IF *weight* is LBW AND *gestational age* is VPT THEN *Risk* is HR.
3. IF *weight* is VLBW AND *gestational age* is PT THEN *Risk* is HR.
4. IF *weight* is LBW AND *gestational age* is PT THEN *Risk* is LHR.
5. IF *weight* is IBW AND *gestational age* is PT THEN *Risk* is LR.
6. IF *weight* is NBW AND *gestational age* is PT THEN *Risk* is LR.
7. IF *weight* is VLBW AND *gestational age* is T THEN *Risk* is LHR.
8. IF *weight* is LBW AND *gestational age* is T THEN *Risk* is LR.

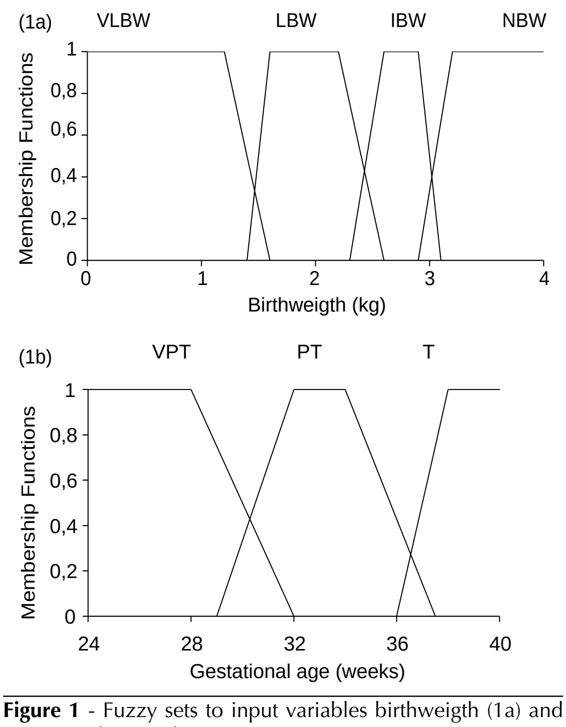

Figure 1 - Fuzzy sets to input variables birthweigth (1a) and gestational age (1b).

Note that, by combining all possible inputs it is possible to build 12 rules, but it was considered relevant only 10 rules, since there are situations that in fact cannot occur. For instance, it is impossible for a very pre-term newborn to have a normal birth weight or insufficient birth weight. Normally an infant in this situation is born at low or very low birth weight. Although this is mathematically possible, it was subtracted from the rule bases, reducing the number of the rules.

The procedure of the fuzzy linguistic model, given two of the above inputs for any child, consists of calculating the membership degree of these values in all fuzzy sets of *birth weight* and *gestational age*. Next, the risk of neonatal death is determined by inference of the fuzzy rule set, using Mamdani's inference and defuzzification of the fuzzy output. The system was run in a Matlab software.

RESULTS

The fuzzy sets related to the linguistic variables *birth weight* and *gestational age* are presented in Figures 1a and 1b, respectively.

It is important to note that this membership function represents the degree of compatibility of some input to all categories rather the probability of this input be classified in any category. In fact, the membership degree represents the *possibility* that the input belongs to the set. Figure 2 shows the membership functions of the output variable *risk of neonatal death*.

The model was run using several values of the input variables and Figure 3 presents the results of the mapping of the system.

It can be noted in this graph that the risk of neonatal death decreases monotonically when birth weight or gestational age increases, as expected. The *inconsistent region* in this figure corresponds to the excluded

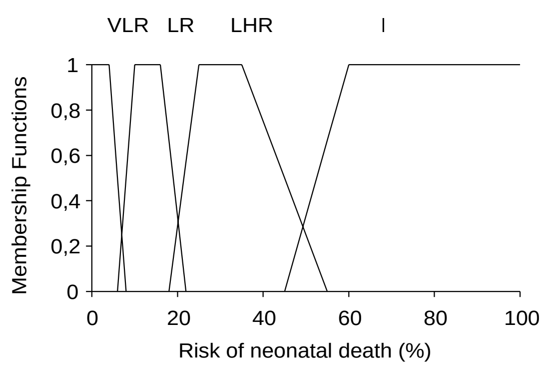

Figure 2 - Fuzzy sets to output variable risk of neonatal death.

rules discussed above. It means that it is impossible to have, for instance, a newborn with a birth weight of 3,200 g born at a gestational age of 30 weeks or a newborn with a birth weight of 4,000 g born at a gestational age of 34 weeks.

In order to validate the model, the cases presented in Table were evaluated by four other experts and applied to the model for the comparison of results. The Spearman correlation coefficient between the model results and the experts' opinions ranged from 0.91 to 0.97. Considering the average of experts' opinions and model results it was found a Spearman correlation coefficient equal to 0.96. Table presents the risk values of neonatal death provided by the average of experts' opinions and the model. Figure 4 shows the correlation between these values.

As it can be noted from the Figure 4, the fuzzy model based in only two input variables was sufficiently robust to determine the risk of neonatal death when compared to experts' performance.

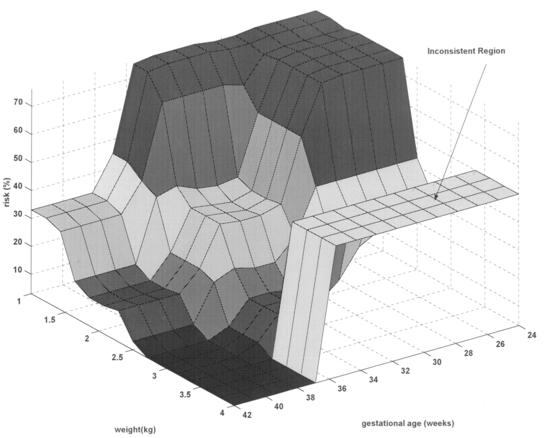

Figure 3 - Surface found by mapping of fuzzy linguistic model to evaluate the risk of neonatal death.

Table - Some hypothetical situations with birthweight (in grams) and gestational age (in weeks) and the experts (means) and model estimated risks (in percent).

Weight (g)	Gestational age (weeks)	Risk of expert (mean) (%)	Risk of model (%)
1,200	28	77,5	76
1,500	30	68,8	65
2,000	34	52,5	33
1,600	36	41,3	35
2,200	36	23,8	35
2,000	38	13,8	13
2,500	38	8,8	6
1,500	36	38,8	50
3,000	40	3,8	3
2,800	39	4,3	4
2,950	37	4,3	5
1,500	32	60,0	47
2,600	39	7,0	3
3,500	40	4,0	3
800	29	88,8	76

DISCUSSION

Neonatal mortality is a main component of childhood mortality.[13] A means of to identifying newborns with high risk to neonatal mortality can offer information to physicians who attend these newborns for them to take actions and prevent devastating outcomes. In the existing literature there are not references of studies approaching this issue in a fuzzy sets theory context.

In this study it was proposed a fuzzy linguistic model to evaluate the risk of neonatal death based on birth weight and gestational age. In the fuzzy approach, one element can fit into two or more classes with different membership degree and it is important to mention that the sum of membership degree does not make 1, in a clear opposition to probability theory. The fuzzy approach also considered inherent uncertainties of the classification process, such as in the classification of a newborn with 2,495 g and another one with 2,505 g, who are classically classified as LBW and IBW respectively. In this fuzzy approach these newborns simultaneously fit into LBW and IBW with some membership.

Furthermore, in logistic regression there is a need of a considerable number of records to establish an association between the outcome, neonatal death, and determinant variables, such as birth weight and gestational age. In fuzzy model, as presented here, there is not necessary.

The model provided good results when compared with the mean values obtained from several experts. The advantage of the risk estimator presented is that the model values do not change with time, which it is not true for experts' opinions. In fact, the experts could provide different values for death risk under the same conditions, depending on their positive or negative feelings. It is common to get from experts different

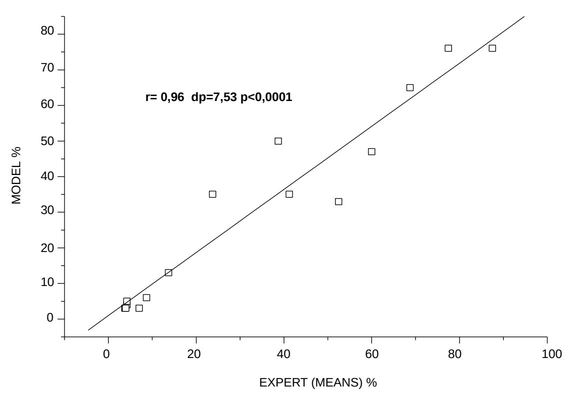

Figure 4 - The correlation between fuzzy model and experts values to risk of neonatal death.

answers for the same question in a week time. In this sense, the model presented here could offer a standardization of the classification process.

In addition, this model avoids the variability in the analysis of newborn conditions provided by different health professionals, which could yield inequalities in the treatment. Besides, the fuzzy model is very simple and implies in low computational expenses, making it possible an easy and inexpensive implementation, features that have an important role in developing and poor countries. In cities where there are no experts available, the model can help understanding and evaluating the risk of neonatal death based only on information regarding the gestational age and birth weight. This is available even in very modest conditions.

As expected, the agreement between the model and experts is improved in extreme situations, since there are less uncertainties in these cases. For instance, when birth weight and gestational age are optimal or when birth weight and gestational age are very critical there are few doubts about the expected outcome. On the other hand, when birth weight and gestational age are in intermediate (doubtful ones), experts provide conflicting opinions as a result of their feelings and personal experiences. However, despite these divergences, the correlation is still very strong with a $p<0.0001$ significance level.

Expecting that the model could be improved with the introduction of new variables, such as Apgar score, previous report of stillbirth and unsuccessful pregnancy is natural and should be encouraged. However, it is important to bear in mind that the number of fuzzy rules grows exponentially and this can impair the model performance. Besides, the inclusion of new variables does not guarantee the improvement and robustness of the model.

The application of fuzzy sets theory in biomedicine and, particularly, in pediatrics, is a new area of research. Nevertheless, this approach has provided promising results in several medical applications, proposing a paradigmatic shift of the healthy sciences.[10,11] The fuzzy model proposed in this paper represent a modest contribution to this changing scenario, since the results show that the fuzzy sets theory can be a powerful tool, in addition to the already existing, to estimate neonatal mortality and other important health indicators.

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