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A Comparison of the Effective Factors of Preterm Birth Versus Low Birth Weight in Southern Iran Using Artificial Neural Network

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Abstract

Objectives: Infants are one of the most vulnerable social groups whose mortality is considered as the development index of a community and family health status. Since preterm birth (PTB) and low birth weight (LBW) are two most important causes of death in infants and are affected by social and economic conditions and geographical living area, investigation of their important risk factors was the attempt in the present study.

Materials and Methods: The variables during pregnancy of 1102 newly delivered mothers referred to Shiraz (southern Iran) University's hospitals were gathered to analyze their effects on birth weight and gestational age of their infants. Artificial neural network (ANN) method was utilized to determine and rank the effective factors on PTB and LBW separately. The performance of ANN model was evaluated by sensitivity, specificity, accuracy and the area under the receiver operating characteristic (ROC) curve. In addition, the amount of increase of mean squared errors (MSEs) in the trained network was considered as the ranking criterion.

Results: Some differences in effective factors of these two pregnancy outcomes appeared. The first three important risk factors were consumption of iron, abortion history and hyperthyroidism for PTB and gestational age, consumption of iron and number of pregnancies for LBW respectively.

Conclusion: The results confirmed the proper performance of ANN method. PTB may be more dependent on the mothers' habits or internal factors while LBW depends on the mothers' history and external factors.

Keywords: Preterm birth, Low birth weight, Artificial neural network, Receiver operating characteristic.

Introduction

Preterm birth (PTB) is an unfavorable and unfortunately frequent result of a pregnancy in the countries. Its prevalence is reported 11%-12.9% in the world (1). The concept of preterm refers to an infant born earlier than 37 weeks of pregnancy. The main cause of PTB is unknown. However, risk factors such as infections, smoking, hypertension, low body mass index, low educational level and drug consumption of mothers and working during pregnancy are reported as effective factors in PTB (2). PTB leads to more than 80% mortality of infants in the third world countries (3).

The other important problem in infants is low birth weight (LBW). An infant with birth weight less than 2500 g is called LBW. The mortality of LBW infants is 40 times more than normal weight ones (4). The primary causes of LBW are PTB, intrauterine growth restriction or their combination (5). Some other significant factors in this event include race, low socio-economic status, low height, malnutrition and low weight of the mother accompanied with the history of LBW, uterine or cervical anomalies, first delivery, chronic disease, smoking, twin or multi births, anemia, etc (4).

To prevent these events, determining the effective factors is important through up to date etiological studies. In addition, since these factors are affected by social and economic conditions and geographical living area, identifying local factors is necessary.

Various researches have previously been conducted on this topic in Iran (4,6-9) and all over the world (1-3,10-17). Most of them have utilized logistic regression to find the significant factors. The other modeling methods were rarely applied (10, 15). The attempt in the present study was to use the high modeling performance of artificial neural networks (ANNs) method in modeling complex relations to investigate the effective factors in PTB and LBW in Shiraz, southern Iran.

Materials and Methods

Dataset

The pregnancy information of 1102 newly delivered mothers referred to Shiraz (southern Iran) University's hospitals for delivery was gathered during a period of three months (September to December 2015). This data included gestational age, mother's disease such as diabetes, Cardiovascular, hypothyroidism, hypertension, kid-

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ney disease and preeclampsia, epilepsy, first trimester bleeding, rupture of the water bag, polyhydramnios, oligohydramnios and other histories and symptoms (Table 1). Based on gestational age and birth weight of infants, two binary response variables (outputs) were defined for two separate modeling processes including PTB (a pregnancy less than 37 weeks) and LBW (an infant with weight less than 2500 g). In each model, the quantitative variable corresponding to the response variable had been removed from independent variables' set (inputs).

Statistical Analysis

ANNs are the branch of artificial intelligence. Their models are inspired by the neural systems of human brain. Recently, ANNs become a very popular model to diagnose the disease. However, they can be over-fitted for training data, and time consuming because of computational requirements (18). But compared to logistic regression analysis, neural network models are more flexible (19). In this study, we used a type of neural network, namely feed-forwards network, with back propagation algorithm to model the relations among variables in our clinical dataset. The aim in a feed-forward back propagation neural network is to predict the output for any given inputs so that the distance between the target and predicted output becomes minimized. This algorithm repeatedly examines all the training data to update its weights. The weight assigned to each input was adjusted during training and the process was only in the forward direction through the network without any feedback loops (19). Ten-fold cross validation method was used for the model's validation. To rank the input variables weighted by the final network, change of mean squared error (MSE) was used so that the total value of MSE (for the model with all input variables) was computed for the final validated model. Then, an input variable was omitted in each step and the MSE of a final model without that variable was calculated and subtracted from the total MSE. The amount of increase in MSE by omitting each variable from modeling process indicates the importance of that variable in the output.

The performance of this modeling method was evaluated by four criteria including sensitivity, specificity, accuracy and the area under the receiver operating characteristic (ROC) curve. In addition, the significant risk factors of these pregnancy outcomes and their ranking were clinically discussed.

Results

A total of 1102 newly delivered mothers in Shiraz University hospitals were considered in this research. Their information and gender, weight and height of infants were used in the modeling methods. The mothers' mean age was 28.7 ± 5.7 (SD). In addition, 1047 (95%) of deliveries were single fetus and only 52 (4.7%) of them were employed mothers. Gestational age of the infants was calculated based on a reliable sonography results in pregnancy period. Tables 1 and 2 summarizes the descriptive statistics of the variables applied in modeling process.

ANN method with feed-forward back propagation training algorithm was utilized and 10-fold cross validation method was used. Four performance criteria were calculated for the final model (Table 3). Figure 1 compares the ROC curve of the two models for PTB and LBW. In addition, risk factors determined by each model were ranked. The amount of increase in MSE by eliminating each variable was applied to order them in both models (Table 4).

Discussion

In present study, the prevalence of PTB was 24.3%. While in the United States is reported 12%–13% and in Europe and other developed countries, reported rates are generally from 5% to 9% (20). Of course, the sample used in our study was conducted in tertiary hospitals. Therefore, the prevalence of PTB was reported high. Also, the results of the present research revealed 15.1% rate for LBW birth in Shiraz, southern Iran. However, in previous studies the rate for LBW was lower than the present study (21,22).

To the best of our knowledge, no study compared the effective factors of PTB and LBW or ranked the importance of these factors through a theoretical method. In present study, this study had two scientifically interesting aspects. First, it compared the effective factors on PTB and LBW by two independent modeling processes in the same data set. Second, most of the previous studies utilized logistic regression in this subject (6-8,12-15,23). Although logistic regression analysis is computationally simpler and more interpretable, its assumptions on data set such as enough sample size in both responses' categories with Bernoulli probability distribution and the number of input variables cause some problems in practice. In contrast, ANN method is more flexible to data circumstances and powerful in modeling but more difficult to interpret.

The risk factors determined for both pregnancy outcomes in the present research almost confirm the results of previous studies. However, there were some differences. For instance, although the good performance of our model were confirmed by all four validity indexes, some important variables have been determined by clinical texts and previous researches (7,10,14,15) such as mothers' age,

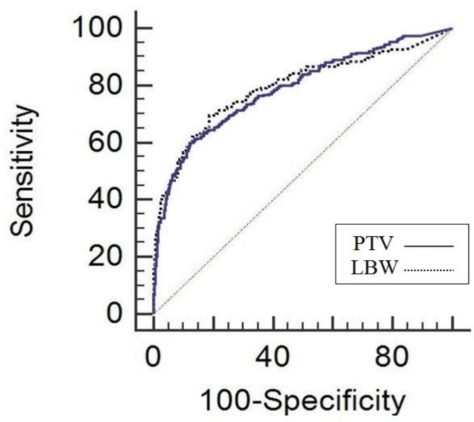

Figure 1. ROC Curves of 2 Models by ANN Method.

Table 1. Descriptive Statistics of Qualitative Variables

Variables	No. (%)	Variables	No. (%)
Gestational diabetes		A history of premature birth	
Yes	88 (8)	Yes	55 (5)
No	1014 (92)	No	1047 (95)
Epilepsy		A history of low birth weight	
Yes	2 (0.2)	Yes	60 (5.4)
No	1100 (99.8)	No	1042 (94.6)
Cardiovascular disease		A history of baby with congenital abnormalities	
Yes	4 (.4)	Yes	28 (2.5)
No	1098 (99.6)	No	1074 (97.5)
Hypothyroidism		Consumption of antibiotics during pregnancy	
Yes	42 (3.8)	Yes	412 (37.4)
No	1060 (96.2)	No	690 (62.6)
Hyperthyroidism		Mother's job	
Yes	16 (1.5)	Housewife	1050 (95.3)
No	1086 (98.5)	Employee	52 (4.7)
Hypertension		Father's job	
Yes	89 (8.1)	Free	7 (0.7)
No	1013 (91.9)	Employee	1095 (99.3)
Kidney disease		Domestic violence	
Yes	2 (.2)	Yes	7 (0.7)
No	1100 (99.8)	No	1095 (99.3)
Other diseases		Baby gender	
Yes	168 (15.2)	Girl	508 (46.1)
No	934 (84.8)	Boy	594 (53.9)
First trimester bleeding		Consumption of iron during pregnancy	
Yes	70 (6.4)	Yes	1072 (97.3)
No	1032 (93.6)	No	30 (2.7)
Rupture of the water bag		Consumption multivitamins during pregnancy	
Yes	47 (4.3)	Yes	849 (77)
No	1055 (95.7)	No	253 (23)
Polyhydramnius		Hookah smoking during pregnancy	
Yes	5 (.5)	Yes	26 (2.3)
No	1097 (99.5)	No	1076 (97.7)
Oligohydramnios		Smoking and hookah pregnancy	
Yes	13 (1.2)	Yes	158 (14.3)
No	1089 (98.8)	No	944 (85.7)
Other side effects		Single – multi fetal	
Yes	20 (1.8)	Singleton	1047 (95)
No	1082 (98.2)	Twain	55 (5)
Education of mother		Education of father	
Illiterate	30 (2.7)	Illiterate	39 (3.5)
Primary	178 (16.2)	Primary	138 (12.5)
Guidance	186 (16.9)	Guidance	237 (21.5)
Diploma	495 (44.9)	Diploma	485 (44.1)
College education	213 (19.3)	College education	203 (18.4)
The gap between the current and previous birth		Economic situation	
First child	456 (41.4)	weak	170 (15.4)
Less than 2 years	392 (35.6)	average	733 (66.5)
2-3 years	140 (12.7)	good	199 (18.1)
More than 3	114 (10.3)		
Preeclampsia			
Yes	73 (6.6)		
No	1029 (93.4)		

Table 2. Descriptive Statistics of Quantitative Variables

Variables	Mean ± SD
Age of mother	28.79 ± 5.81
Age of father	32.98 ± 6.08
Mother's height	161.49 ± 6.69
Number of pregnancies	2.16 ± 1.16
Birth	1.86 ± 0.92
The abortion	0.31 ± 0.65
The number of living children	1.81 ± .89
Pre-pregnancy weight	63.2 ± 10.18
The amount of hemoglobin in the first prenatal visit	12.24 ± 1.12
Mother's weight in weeks 38-40	76.32 ± 11.25
Birth weight	3057 ± 609
Birth height	49.18 ± 3.72
Gestational age	265.9 ± 17.9

Table 3. Performance Indexes of ANN Method for 2 Models

Performance Index	PTB	LBW
Sensitivity	81.07	87.84
Specificity	82.79	87.82
Accuracy	81.36	87.82
The area under the ROC curve	0.78	0.79
P value	<0.001[a]	<0.001[a]

Abbreviations: PTB, preterm birth; LBW, low birth weight; ROC, receiver operating characteristic; ANN, Artificial neural network.
[a] Significant at 0.001.

Table 4. The Order of ten First Important Variables in Each Pregnancy Outcome According to the Amount of Increase in MSE by Eliminating Each Variable for ANN model

Variables' Order	Pregnancy Outcome	
	PTB	LBW
1	Consumption of iron	Gestational age
2	Abortion history	Consumption of iron
3	Hyperthyroidism	Number of pregnancies
4	Hookah smoking during pregnancy	Father's level of education
5	Hookah smoking before pregnancy	Other complications
6	The number of living children	The number of living children
7	Hypertension	Baby gender
8	Age of father	Mother job
9	Hb in the first prenatal visit	Epilepsy
10	Baby gender	Polyhydramnios

Abbreviations: PTB, preterm birth; LBW, low birth weight; ANN, Artificial neural network; MSE, mean squared error.

education and diseases were not in the list of first ten effective variables on PTB and LBW. In addition, the results are a little different from the previous study in Shiraz for 6 years ago (9). Perhaps, differences in social and economic conditions, life style and geographic climate affect the pregnancy outcomes or our powerful modeling method and enough sample size leads to more validated results. An interesting result of the present study was the different orders of effective variables on PTB and LBW. Accordingly, PTB may be more dependent on the mothers' habits or internal factors while LBW depends on the mothers' history and external factors.

Conclusion

All four performance indexes confirmed the appropriateness of ANN method in the present study. However, one limitation of this study was data gathering from hospital records and visiting checklists during pregnancy in a cross sectional study. Hence, mothers had been visited by different physicians during their pregnancy and their information might not be accurate. In addition, the random sample was taken from the referees to the three governmental hospitals affiliated to Shiraz University of Medical Sciences. Most of them are of low or middle socio-economic status. Therefore, to compare the effective factors on these pregnancy outcomes more precisely, a longitudinal study is suggested to investigate other important variables such as the changes of mothers' weight, nutrition and nausea, vomiting and other pregnancy complications along with biochemical blood factors like zinc, folic acid and inflammatory factors on a cohort.

Ethical Issues

We have no ethical issues to declare.

Conflict of Interests

None.

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