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Artificial Neural Networks for Analysis of Factors Affecting Birth Weight

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Abstract

Objective: This work present 2017 data on births in Beykoz according to a wide variety of characteristics. Factors affecting birth weight (BW) of newborn were examined with Artificial Neural Network (ANN). Method: There are 19 independent variables and one dependent dichotomous variable that form a database. These data were obtained from 223 samples. For this study, the analysis method used is ANN. Results: The variables as gender of the baby, maternal age, Body Mass Index (BMI), nutrition habits, mother's education, gestational age, maternal pre-pregnancy weight, maternal weight gain in pregnancy, mother's alcohol use, mother's cigarette use are considered. These variables have been found to have a significant effect on the BW. Conclusion: In this study, for the BW, a novel system based on ANN is proposed. When a person contacts a physician, it is very important for the physician to accurately estimate whether or not this person has a disease. This is because the physician's estimate is a principal factor in determining whether to discontinue treatment, to obtain more data by testing, or to treat the patient without exposing the patient to the risks of advanced diagnostic tests. It is believed that the prepared ANN system may be useful for physicians to make decisions about factors affecting the BW of babies during pregnancies. The results show that ANN system based a learning method can assist in the predict of BW.

Keywords

Artificial Neural Network, Birth Weight, Newborn, Levenberg–Marquardt Algorithm, Odds Ratio

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1. Introduction

Nowadays, Fuzzy Sets Theory (FST), a useful tool, is used in every field of medicine from public health to surgical systems, from medical imaging to diagnostic systems. Imprecision, uncertainty and vagueness are widespread in medical science. FST has been improved using all values between true and false (or 1 and 0), and has become a potential instrument for cope with uncertainty and imprecision. When variables are given linguistically, these variables with FST can be comfortable and easily studied, simplify understandable, reduce the computational costs. There is also the capability to build systems into human expert experience. FST make this approach a highly exciting option to detailed medical models.

There are a wide variety of NN models which have been advanced which assists physicians in diagnosing the patients more correctly and accurately. NNs make a very generic path of approaching problems. The output of the network represents types of data which can be divided into groups, that is it consists of categorical variables. Therefore, it is performing prediction and when the output has discrete values, and then it is doing classification.

Numerous NNs used in disease diagnosis are available in the

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literature. When studies in the literature are examined, it can be seen that with ANNs, most of the early preterm infants can accurately predict the risk of death.

BW is the initial weight immediately measured when the baby is born. BWs of healthy babies can range from 2500gr to 4500gr. An infant with a low birth weight (LBW) may be born prematurely or it may be born smaller than normal. Even, LBW infants can be both small and premature. Some LBW babies may be more at risk for certain health problems. Some of the LBW babies may become sick and develop infections in the first days of their lives. In the first days of life, infants who not have these problems may also have long-term problems such as social development and learning disorders. One of the most important factors affecting perinatal morbidity and mortality is the BW of the baby. The birth of the baby on the ideal BW will reduce the perinatal risk. However, BW is a major determinant of infant morbidity and mortality.

Infants born with LBW are more vulnerable to death because they are not immaturity, and this is considered a very important health index [1]. In the literature, the relationship between LBW and infant mortality has been clearly demonstrated. This is the reason why the factors affecting the BW are primarily studied in terms of public health. Many different risk factors have been studied that affect BW. Variables affecting BW are mainly socioeconomic, physical, medical, ethnical and anthropometric categories. Investigating the relationship between one or more of these parameters and the BW will have important consequences. Therefore, it is thought that the factors that may cause babies to be born at LBW and their correction are thought to reduce perinatal morbidity and mortality.

Given the birth outcomes, LBW appears to be a serious problem, especially in developing and undeveloped countries. World Health Organization (WHO) data shows that more than 20 million infants in the world are born LBW, annually. When LBW infant incidence is examined according to the continents, it is seen most in Asia (18.3%) and least in Europe (6.4%). According to WHO data, LBW infant incidence is 18,6% in undeveloped countries, 16,5% in developing countries and 7.0% in developed countries.

The main source of data for this study is the live births in Beykoz, Gumussuyu Health Center (BGHS). The Data have been analyzed using Neuro-intelligence tool. The model proposed in this study has the potential to predict the BWs of newborn infants.

2. Material and Method

2.1. Criteria for Considering Studies for This Paper

2.1.1. Type of Study

In this study, factors affecting BW from birth records between January 2017 and December 2017 were examined.

2.1.2. Selection of Area and Samples

A database was created from the Beykoz District in Istanbul. The records that make up the database consist of the information of the infants followed up by the "Family Medicine System" in BGHS. Records with incomplete information in the dataset have been eliminated.

Beykoz is a relatively rural area in Istanbul. People living in Beykoz usually occur families who have migrated from Anatolia to Istanbul. The lifestyle in Beykoz is mostly rural life rather than urban life. The habits of the people in Beykoz are the cultural lives of the regions where they emigrate. The lives of the people in Beykoz continue according to their economic conditions and lifestyles. Therefore, the life in Beykoz is closer to the disadvantaged zone status.

There are 250,410 people living in the district of Beykoz. The population of the Gümüşsuyu neighborhood is 14.306. Gümüşsuyu is the second most populous neighborhood of the Beykoz district.

It will be useful to examine the impact of the lifestyle of the people living in the rural area on their health. Therefore, the samples of the work consisted of 223 babies born in the Gümüşsuyu neighborhood of Beykoz in Istanbul between January 2017 and December 2017.

2.1.3. Types of Study Variables

There are 19 independent variables and one dependent dichotomous variable (BW) that form a database. These data were obtained from 223 samples.

The 19 independent variables used in constituting the database are gender of the baby (GB), maternal age (MA), Body Mass Index (BMI), gravida (Gr), parity (Par), nutrition habits (NH), inter-pregnancy interval (IPI), mother's education (MsE), father's education (FsE), antenatal care (AC), gestational age (GA), maternal pre-pregnancy weight (MPPW), maternal weight gain in pregnancy (MWGP), mother's working status (MsWS), income level (IL), mother's alcohol use (MsAU), mother's cigarette use (MsCU), mother's caffeine use (MsCafU), mode of delivery (MD).

From these variables, "antenatal care" has been abolished since each sample cannot be obtained with the correct information. In the same way, this variable has also been eliminated because sufficient and accurate information cannot be obtained about "mother's use of caffeine". In this study, outcome variable is the BW of the baby. Table 1 shows how these variables are selected:

Table 1. Definitions of independent variables.

Variable	Definition (Coding)
GB	Male (1), Female (2)
MA	19-25 (1), 25-35 (2), 35+ (3)
GA	<37 (1), >37 (2)
Gr	1-4
Par	1-4
NH	regular (1), irregular (2)
IPI (month)	0-72
BMI	<18.5 (1), 18.5-24.99 (2), 25.0-29.99 (3), >30 (4)
MPPW (kg)	48-65 (1), 65+ (2)
MWGP (kg)	5-11 (1), 11+ (2)
MsAU	Use (1), No Use (2)
MsCU	Use (1), No Use (2)
MD	Normal (1), C-section (2)
MsE*	P (1), S (2), H (3), U (4)
FsE*	P (1), S (2), H (3), U (4)
MsWS	Working (1), No Working (2)
IL (monthly)	<$1000 (1), $1000-$3000 (2) $3000+ (3)

*P: Primary, S: Secondary, H: High, U: University

The World Health Organization categorized BMI [2]. It used metric units (kilograms and meters – kg/m^2) to calculate the BMIs. For BMI ≥ 30, Obese Class was evaluated as a single class.

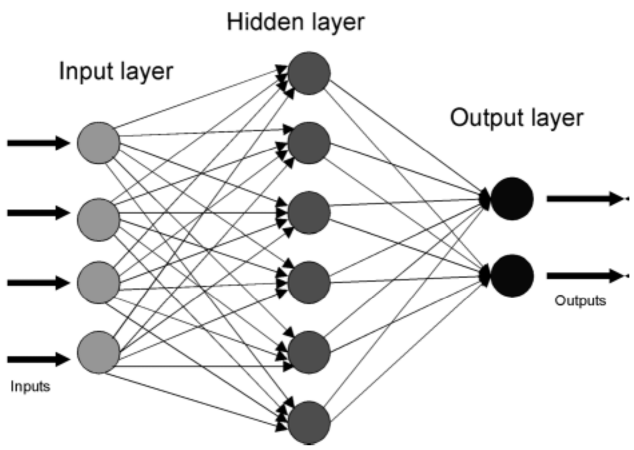


Figure 1. Neural Network Model – Layers: Input, Hidden, Output.

2.1.4. Type of Analysis

The analysis method used in this study is ANN. After collection, data were checked, verified, edited and entered into MATLAB 2015b.

ANNs, one of the research fields of artificial intelligence science, includes studies on learning computers. Today, computers and computer systems have become indispensable parts of our lives. Computers have gained the ability to summarize large amounts of data over time and comment on events using this data, while only accounts or data transfers can be made in the past years. Nowadays, computers are able to make decisions about events and to learn the relationship between them. Problems that cannot be formulated mathematically and cannot be solved can also be solved by computers.

Thanks to their learning features, ANNs are able to provide solutions to the problems that are too complex for traditional techniques. Again, thanks to their learning ability, they can make generalizations in previously unexplored situations using known examples. In ANNs information storage is done with training samples using the training feature provided. With trial and error, the network learns how to do the job on its own. An ANN learns by evaluating the changes in the input set and produces an output to it. The learning process takes place with a learning algorithm that will produce the same output for similar input sets. Training of networks found analogous to nervous structures is similar to the training of a normal livings. The separation of classes from each other is achieved by the stepwise processing of the information taken from the sample set by the learning algorithm. Using ANNs, machines have acquired the abilities such as learning, generalization, classification, estimation and perception.

With the development of computer technology, human beings do almost all of their processing on these innovative technologies and enable new methods to be found. The definition of artificial neurons was first given by McCulloch and Pitts [3]. After these initial definitions, the rapid progress of information technology affected the development of NNs. In the 1980s, the idea that a machine could be thought of as a human being was introduced, and in the 1990s Artificial Neural Networks technology developed rapidly [3-5].

NNs are algorithms produced by sampling the shape of the human brain. NNs can collect information about samples, make generalizations, and then decide on those samples using information learned in comparison with samples that they have never seen before. Because of these learning and generalizations, NNs find wide application in many scientific fields and demonstrate their ability to solve complex problems successfully. NNs according to another definition, parallel and distributed information processing structures, which are inspired by the human brain, interconnected by weighted links and each comprising processing elements having their own memory, in other words, computer programs that mimic biological neural networks.

The advantages of using NNs can be expressed as follows:

* Set the rules by giving input and output information during learning.

* Benefit from experience.

* The calculation is cumulative, asynchronous and parallel after learning.

* Memory is allocated and spread out over the network.

* There is error tolerance.

Artificial neural networks are a class of nonlinear regression and discrimination statistical methods. They are of proven value in many areas of medicine. They do not require a priori information regarding the phenomenon, and they make no distributional assumptions. When the appropriate method is used to avoid over fitting (i.e., loss of generalization by fitting the patterns to the test data too precisely), artificial neural networks are usually at least as accurate as classical statistical models, and, depending on the complexity of the phenomena, they can be much more accurate.

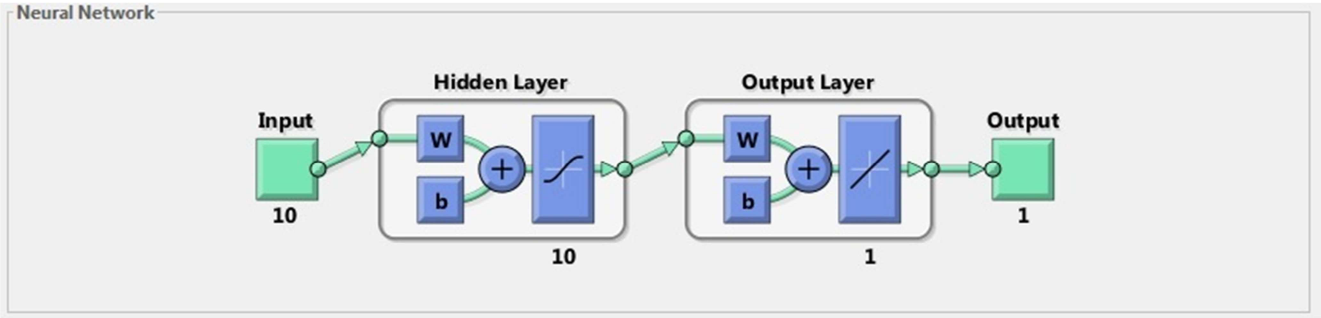


Figure 2. Our Neural Network Structure.

As also shown in Figure 2, in our model, the number of hidden neurons is 10. The data were divided into the sets such as for training 70%, for validation 15% and for testing 15%. Levenberg-Marquardt algorithm is chosen for training and Mean Squared Error is chosen for performance.

2.2. ANN Applications in Medicine

Because of the significantly flexibility of input data, ANNs have proven helpful in medicine. ANNs have various applications in medical science [6-12].

Itchhaporiaa et al. [7] characterizes the computer technology of ANNs and investigates the usage of ANN technology in clinical cardiovascular research. Amato et al. [13], study and discuss the philosophy, capabilities, and limitations of ANNs in medical diagnosis. In this discuss, medical diagnosis examples such as cardiovascular diseases, cancer, diabetes are presented. The method of classifying cancers to specific diagnostic categories based on their gene was developed using ANNs [10]. Wang et. al. [14], improved an ANN model. The model can be used to fast detect those at high risk of Type 2 Diabetes Mellitus, and monitor undiagnosed Type 2 Diabetes Mellitus patient in rural adults using demographic, lifestyle, and anthropometric data.

Firstly, the authors describe the fundamentals of NNs and then discuss the main application fields of NN technology in medicine, in [15]. Baxt [6] discussed the applications of NN in medicine and gave some examples such as myocardial infarction, analysis of plain radiographs of focal bone lesions, waveform analysis. Multilayer NN, probabilistic NN and learning vector quantization NN results were obtained for thyroid disease diagnosis and these results were compared. It is seen that the results obtained are better than the results presented in previous studies [16].

A geometrical interpretation of fuzzy sets using points in a fuzzy hypercube is given [17]. Using this geometric interpretation, fuzzy logic applications in medicine and bioinformatics are explained [18]. Er et al. [19], used the ANNs for diagnosis of tuberculosis. Dey et al. [20], used an ANN software program located on the market to differentiate between prognostically good and bad chronic myeloid leukemia cases. An AAN model is built for the detection of carcinoma in effusion cytology [21]. Devi et al. [22] discussed NNs architectures related to the cervical cancer for detection methods at the earliest stage.

A new intelligent method in the clinical diagnosis of thoracic lung cancer surgery is proposed, that helps doctors in patient selection and identifies the risk of death in patients after surgery [23]. One of the causes of adverse neonatal outcomes is maternal obesity. Therefore, at the end of pregnancy, ANN models based on maternal weight status and clinical data have been developed to estimate reliable maternal blood concentrations of oxidative stress and adipokines biomarkers [24].

3. Results and Discussion

One of the contributing factors to the United Nations Millennium Development Goals is to reduce the low BW and child mortality of babies born. Baby's BW is affected by many variables. Knowing and correcting factors that negatively affect BW will significantly reduce the risk of perinatal morbidity and mortality as well as BW in the baby.

In Turkey, the reforms and infrastructure services in the field of health in the last 15 years has created great developments in the society and individual health. With the establishment of the "Family Medicine System", all the people of the society have attained much faster and better quality health services. Thanks to the "Family Medicine System", a doctor has been assigned to every citizen and the health status of people has become more controllable. Thus, in the development and organization of health services, the delivery of preventive and therapeutic health services to individuals has become more qualified. Due to these developments, the rate of child mortality and maternal mortality declined significantly. Every year about one million three hundred thousand babies are born, in Turkey. One hundred and thirty thousand of these babies are born prematurely before they fill their regular time.

In this study, various factors affecting BW were examined. Beykoz, a rural region for the study, was chosen. The mean of mothers who are first birth 39,46%. The averages are given in Table 2.

Table 2. Averages.

Variable	Average
BW (gr)	3130, 45
MA (year)	29,74
GA (week)	38,2
BMI (kg/m^2)	25,3
MPPW (kg)	66
MWGP (kg)	13,7

The logistic regression analysis showed that variables GB, MA BMI, NH, MsE, GA, MPPW, MWGP, MsAU, MsCU were factors affecting the BW (Table 3). IBM SPSS Statistics 21 was used for logistic regression analysis.

Table 3. Odds Ratio Values.

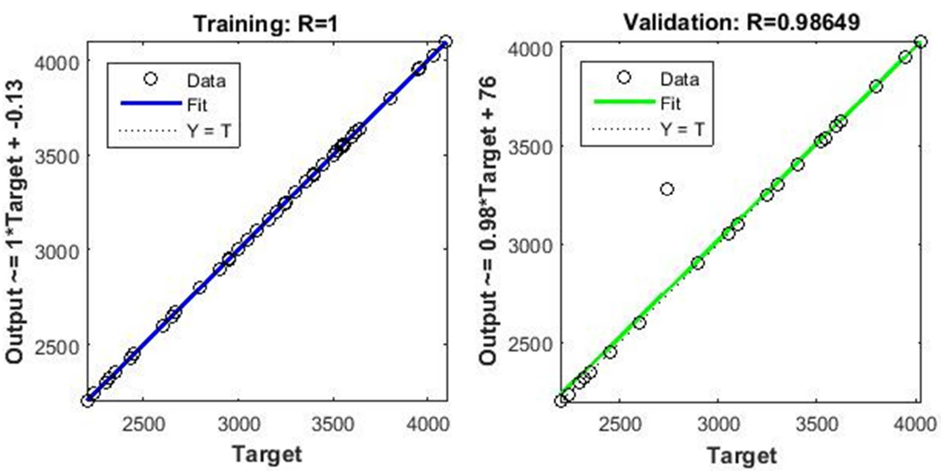
		OR	*95% CI*	*P value*
1	GB	5,28	4,80-6,97	0.0001
2	MA	1,04	0,86-1,09	0.002
3	GA	9,12	8,79-10,98	0.0001
4	Gr	*	*	NS
5	Par	*	*	NS
6	NH	1,10	0,94-1,26	0.0026
7	IPI	*	*	NS
8	BMI	1,62	0,97-2,75	0.003
9	MPPW	2,51	1,87-3,89	0.0001
10	MWGP	1,41	0,82-2,23	0.02
11	MsAU	8,86	7,23-10,54	0.0001
12	MsCU	9,18	8,42-11,07	0.0001
13	MD	*	*	NS
14	MsE	1,35	0,74-2,48	0.038
15	FsE	*	*	NS
16	MsWS	*	*	NS
17	IL	*	*	NS

OR: Odds Ratio; CI: Confidence Interval; NS: not statistically significant

The most commonly used value in statistical significance tests is P ≤.05; however, such criteria can vary depending on the amount of available data. For example, when the number of observations is very large, predictors with small effects on the outcome can also become significant. To avoid exaggerating the significance of these predictors, a more stringent criterion (eg, P ≤.001) can be used.

The ANN approach has several advantages. It sets input data without any assumptions, and develops a mapping of the input and output variables that can predict desired output. Any smooth, measurable function between input and output can be approximated by multi-layer neural networks through selecting a suitable set of connecting weights and transfer functions. ANN models have been widely applied to medicine. ANNs have been carried out to model factors affecting to BW and forecast BW.

The regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45-degree line, where the network outputs are equal to the targets. For this problem, the fit is reasonably good for all data sets, with R values (Figure 3). The output tracks the targets very well for training, testing, and validation, and the R-value is over 0.95 for the total response.



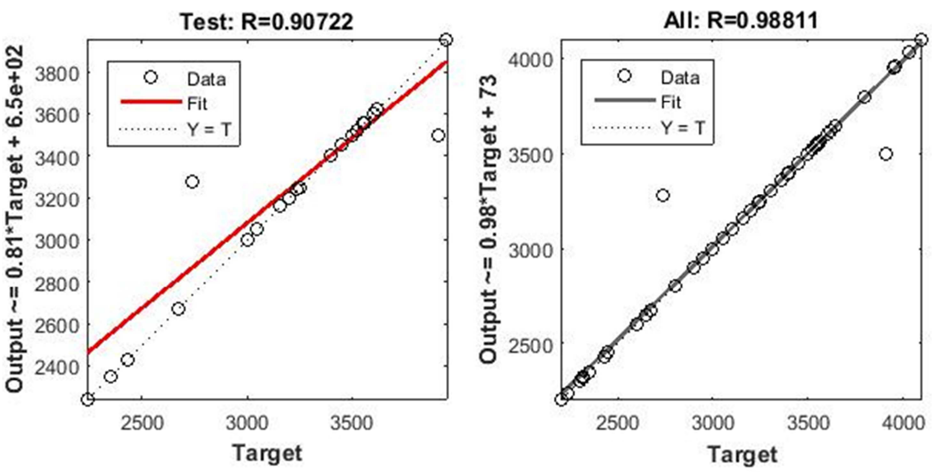


Figure 3. R values.

After the number of hidden neurons is determined, the best network structure with the lowest value of the MSE and the highest value of R is obtained. The equation

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(X_k - Y_k)^2$$

gives the Mean Square Error (MSE), where X_k is value of the simulated data, Y_k is value of the measured data, k is counter and n is the number of measured data. MSE shows the difference between estimated values and real values of the parameters. That is, the MSE compares the estimate values with the actual values. If the values are equal in this comparison, then the MSE is said to be zero. However, the ideal value of the MSE is not zero. Because in this case an excellent prediction is made for the training data. In reality, it is unlikely to predict any data perfectly. As shown in Figure 4, the best line represents the best amount of MSE for the designed network.

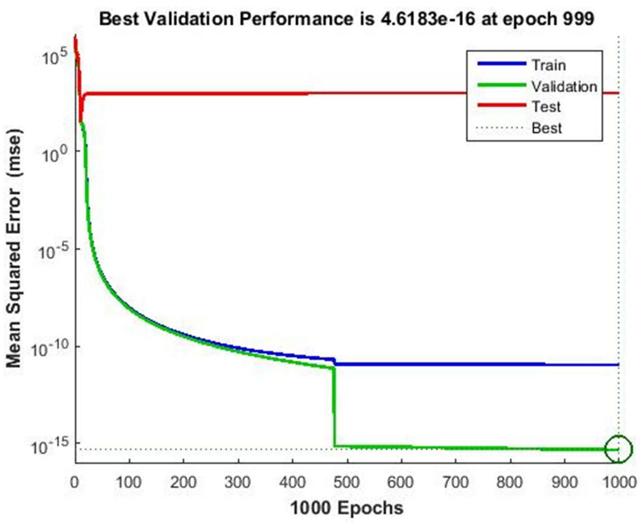


Figure 4. Best performance for neural networks with validation data.

When the values calculated according to the neural network model are compared with the actual values, graphical representation is shown in Figure 3. As seen in this graph, the correlation coefficient is calculated and found as 0.98811. This obtained R value is suitable.

4. Conclusion

ANN was used as analysis in the study. The BWs of the babies of the mothers followed up with a "Family Medicine System" in a rural area were examined.

Neural network has been established of their potentials in many domains related with medical disease diagnosis and other application. Although, Neural networks never replace the physicians instead they can helpful for decision making, classifying, screening and also can be used by domain physicians to cross-check their diagnosis. This ANN model proves the better results and helps the domain physicians and even person related with the field to plan for a better diagnose and provide the patient with early diagnosis results as it performs realistically well even without retraining. As clinical decision making requires reasoning under uncertainty, expert systems and fuzzy logic will be suitable techniques for dealing with partial evidence and with uncertainty regarding the effects of proposed interventions. Neural Networks have been proven to produce better results compared to other techniques for the prediction tasks.

Besides, the ANN 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 physicians available, the model can help understanding and evaluating the risk of neonatal death based only on information regarding variables and birth weight. This is available even in very modest conditions. As expected, the agreement between the model and physicians is improved in extreme situations, since there are less uncertainties in these cases.

The main purpose of model development is to examine the causal relationship between independent and dependent variables. If the main purpose is outcome classification and considerable mutually effects or complicated nonlinearities exist in the data set, then using the ANN can be especially beneficial. ANN is very powerful as a method. That is, ANN does not need a high level of operator decision. Therefore, it uses a sophisticated non-linear model to attain high classification performance.

Baby's birth weight is affected by many variables. Knowing and correcting factors that negatively affect birth weight will significantly reduce the risk of perinatal morbidity and mortality as well as birth weight in the baby. It was observed that the desired information could not be obtained from antenatal care and mother's use of caffeine from selected variables and these substances were eliminated. Gr, Par, IPI, MD, FsE, MsWS and IL variables had no effect on the BW. Other variables (gender of the baby, maternal age, BMI, nutrition habits, mother's education, gestational age, maternal pre-pregnancy weight, maternal weight gain in pregnancy, mother's alcohol use, mother's cigarette) considered have been found to have a significant effect on the BW. The ANN approach for BW has been successful with given independents variables. Our system can be combined with the software of medical decision-making tools. The benefit of such systems is that they help the physician to make decisions without being skeptical.

In medicine, many diagnostic questions can be answered in yes or no, black and white terms. When it comes to determining the best treatment plan for each patient, however, there are many more shades of gray.

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. The ANN 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.

The main aim of this study is to minimize the problems that may arise after the birth by maximizing the birth weight estimation of the physicians in a more effective way with the established model.

Conflict of Interests

The authors declare that they have no competing interests.

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