

Low Birth Weight Prediction Using JNN

Osama Salah El-Din Al-Madhoun, Afnan Omar Abu Hasira, Soha Ahmed Hegazy, Samy S. Abu-Naser

Department of Information Technology,
Faculty of Engineering and Information Technology,
Al-Azhar University - Gaza, Palestine

Abstract: *In this research, an Artificial Neural Network (ANN) model was developed and tested to predict Birth Weight. A number of factors were identified that may affect birth weight. Factors such as smoke, race, age, weight (lbs) at last menstrual period, hypertension, uterine irritability, number of physician visits in 1st trimester, among others, as input variables for the ANN model. A model based on multi-layer concept topology was developed and trained using the data from some birth cases in hospitals. The evaluation of testing the dataset shows that the ANN model is capable of correctly predicting the birth weight with 100% accuracy.*

Keywords: Artificial Neural Networks, Birth Weight, ANN, Predictive Model.

1. INTRODUCTION

Low birth weight (LBW) is defined by the World Health Organization as a birth weight of a infant of 2,499 g (5 lb 8.1 oz) or less, regardless of gestational age.[1] Subcategories include very low birth weight (VLBW), which is less than 1,500 g (3 lb 5 oz), and extremely low birth weight (ELBW), which is less than 1,000 g (2 lb 3 oz) [2]. Normal weight at term delivery is 2,500–4,200 g (5 lb 8 oz–9 lb 4 oz).

LBW is either caused by preterm birth (that is, a low gestational age at birth, commonly defined as younger than 37 weeks of gestation) or the infant being small for gestational age (that is, a slow prenatal growth rate), or a combination of both.

In general, risk factors in the mother that may contribute to low birth weight include young ages, multiple pregnancies, previous LBW infants, poor nutrition, heart disease or hypertension, untreated coeliac disease, drug addiction, alcohol abuse, and insufficient prenatal care. It can also be caused by prelabor rupture of membranes [3]. Environmental risk factors include smoking, lead exposure, and other types of air pollutions.[4-6]

Four different pathways have been identified that can result in preterm birth and have considerable evidence: precocious fetal endocrine activation, uterine overdistension, decidual bleeding, and intrauterine inflammation/infection.[7] From a practical point a number of factors have been identified that are associated with preterm birth, however, an association does not establish causality.

Being small for gestational age can be constitutional, that is, without an underlying pathological cause, or it can be secondary to intrauterine growth restriction, which, in turn, can be secondary to many possible factors. For example, babies with congenital anomalies or chromosomal abnormalities are often associated with LBW. Problems with the placenta can prevent it from providing adequate oxygen and nutrients to the fetus. Infections during pregnancy that affect the fetus, such as rubella, cytomegalovirus, toxoplasmosis, and syphilis, may also affect the baby's weight.

The main objective of a birth weight prediction system is to identify and the weight of the baby, Do you a normal weight or a low weight, and baby's low weight affects her life, such as injury squint.

This study seeks to explore the possibility of using the artificial neural network model to predict the birth weight, at the lowest possible time and high accuracy in the results.

Of course one would expect the birth weight to be associated with several influential factors as mentioned earlier. On the other hand it is clear that it will be very difficult to find a mathematical model that may be an appropriate model for this relationship between performance/factors. However, one realistic method of the weight prediction may be to study data on the background of the some factors [8].

The practical approach to this type of problem is to apply a regression analysis in which data is better integrated into some functions. The result is an equation in which both input x_j is multiplied by w_j ; the sum of all these products is constant, and then an output of $y = \sum w_j x_j + b$, is given, where $j = 0..n$.

The problem here is that it is difficult to choose a suitable function to capture all data collection as well as automatically adjust the output in the case of more information, because prediction is controlled by a number of factors, and this control will not be any clear and known regression model.

The artificial neural network, which simulates the human brain in solving a problem, is a more common approach that can address this type of problem. Thus, attempting to develop an adaptive system such as artificial neural network to predict the temperature based on the results of these factors [9].

1.1 The objectives of this study are:

- To identify some appropriate factors that affects the low birth weight.
- To convert these factors into appropriate models for adaptive system coding.
- Designing an artificial neural network that can be used to predict weight based on some predefined data.

2. THE ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (ANN) is an application of Artificial Intelligence [10]. ANN is an arithmetical model that is motivated by the organization and/or functional feature of biological neural networks. A neural network contains an interrelated set of artificial neurons, and it processes information using a connectionist form to computation. As a general rule an ANN is an adaptive system that adjusts its structure based on external or internal information that runs through the network during the learning process. Recent neural networks are non-linear numerical data modeling tools. They are usually used to model intricate relationships among inputs and outputs or to uncover patterns in data. ANN has been applied in numerous applications with considerable attainment [11]. For example, ANN has been effectively applied in the area of prediction, handwritten character recognition, evaluating prices of lodging [12].

Neurons are often grouped into layers. Layers are groups of neurons that perform similar functions. There are three types of layers. The input layer is the layer of neurons that receive input from the user program. The layer of neurons that send data to the user program is the output layer. Between the input layer and output layer are hidden layers. Hidden layer neurons are only connected only to other neurons and never directly interact with the user program. The input and output layers are not just there as interface points. Every neuron in a neural network has the opportunity to affect processing. Processing can occur at any layer in the neural network. Not every neural network has this many layers. The hidden layer is optional. The input and output layers are required, but it is possible to have on layer act as both an input and output layer [13].

ANN learning can be either supervised or unsupervised. Supervised training is accomplished by giving the neural network a set of sample data along with the anticipated outputs from each of these samples. Supervised training is the most common form of neural network training. As supervised training proceeds the neural network is taken through several iterations, or epochs, until the actual output of the neural network matches the anticipated output, with a reasonably small error. Each epoch is one pass through the training samples. Unsupervised training is similar to supervised training except that no anticipated outputs are provided. Unsupervised training usually occurs when the neural network is to classify the inputs into several groups. The training progresses through many epochs, just as in supervised training. As training progresses the classification groups are “discovered” by the neural network [14].

Training is the process by which these connection weights are assigned. Most training algorithms begin by assigning random numbers to the weight matrix. Then the validity of the neural network is examined. Next the weights are adjusted based on how valid the neural network performed. This process is repeated until the validation error is within an acceptable limit [14].

Validation of the system is done once a neural network has been trained and it must be evaluated to see if it is ready for actual use. This final step is important so that it can be determined if additional training is required. To correctly validate a neural network validation data must be set aside that is completely separate from the training data [13].

About 60% of the total sample data was used for network training in this paper. About 30% of the total sample data served as test and the remaining 10% used for validation of the system.

3. METHODOLOGY

By looking deeply through literature and soliciting the experience of human experts on birth children, a number of factors have been identified that have an impact on the low birth weight. These factors were carefully studied and synchronized in an appropriate number to encode the computer in the ANN environment. These factors were classified as input variables. Configurations variables reflect some possible levels of know birth weight by values and factor[15].

3.1 The Input Variable

The input variables specified are those that can be obtained simply from the hospitals. Input variables are:

Table 1: Attributes of the Data set

No.	Attributes
1.	smoke

2.	race
3.	age
4.	lwt
5.	ptl
6.	History of hypertension
7.	uterine irritability
8.	ftv
9.	birth weight in grams

3.2 The Output Variable

The output variable represents the performance of the hospitals. The output variable depends on the input.

Table 2: Output variables

S/N	Output	Represent
1.	1	low weight
2.	0	Normal weight

3.3 Preprocessing of the Dataset

The features of the Low birth dataset was normalized using the formula $X_i = (X_i - X_{min}) / (X_{max} - X_{min})$. The Yes was converted to 1 and The No was transformed into 0 as shown in Figure 1.

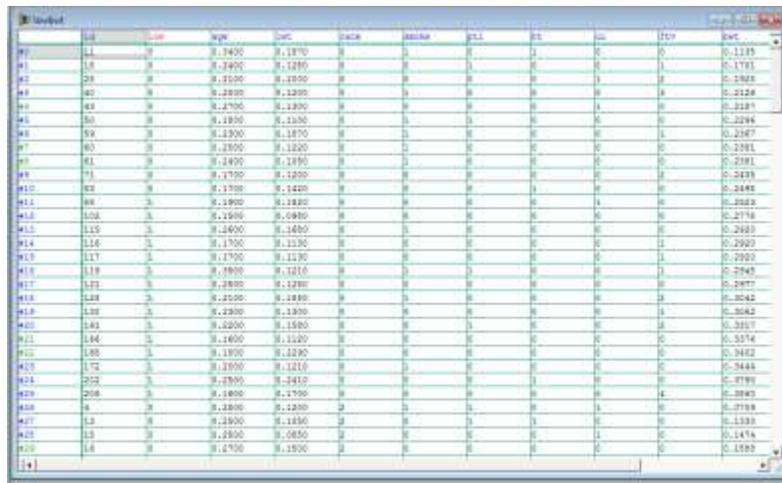


Figure1: Scaled dataset of low birth

3.4 Design of the Neural Networks

The proposed ANN model consists of four layers: one input layer with 10 nodes, two hidden layers with (3 nodes x 2 nodes), and one output layer with one node as seen in Figure 2.

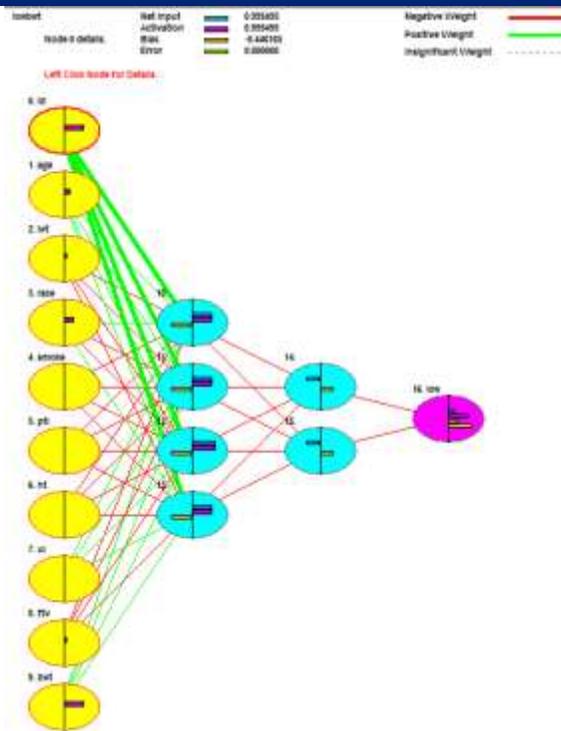


Figure 2: Shows the Design of the Neural Networks

3.5 The Back-propagation Training Algorithm

- Initialize each w_i to some small random value
- Until the termination condition is met, Do
- For each training example $\langle(x_1, \dots, x_n), t\rangle$ Do
- Input the instance (x_1, \dots, x_n) to the network and compute the network outputs o_k
- For each output unit k : $\delta_k = o_k(1 - o_k)(t_k - o_k)$
- For each hidden unit h : $\delta_h = o_h(1 - o_h) \sum_k w_{h,k} \delta_k$
- For each network weight w_j Do $w_{i,j} = w_{i,j} + \Delta w_{i,j}$, where $\Delta w_{i,j} = \eta \delta_j x_{i,j}$ and η is the learning rate.

4. EVALUATION OF THE NEURAL NETWORK

As mentioned previously, the purpose of this experiment was to predict the weight of newborn babies. Where we used data, which provides the possibility to implement and test the neural network and its learning algorithm. Our neural network is a sensor expression designed to detect the presence of one of two sets of materials. Alternatively, human reading may be wrong. Then we set the parameter of the proposed ANN model as can be seen in Figure 3.

After training and validation, the network was tested using the test data set and the following results were obtained. This involves inputting variable input data into the grid without output variable results. The output from the grid is then compared with the actual variable data.

The neural network was able to accurately forecast 100% of the excellent data (representing 8 inputs and based on the inputs.) We have two outputs represented in values and each value is as follows: (0)100% and (1) 100% as shown in Figure 4. We also determined the most influential factors that affect the low birth dataset as shown in Figure 5. Figure 6 outlines the details of the proposed ANN model.

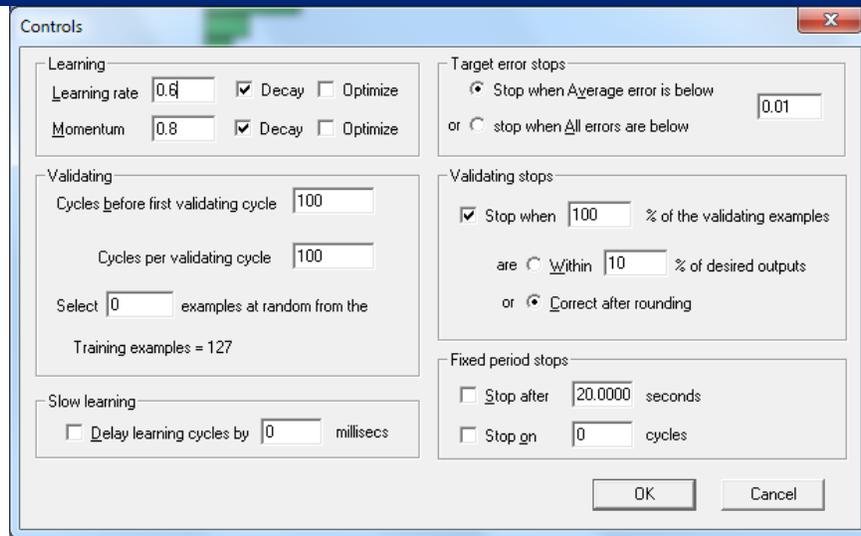


Figure 3: Control of the ANN model parameters

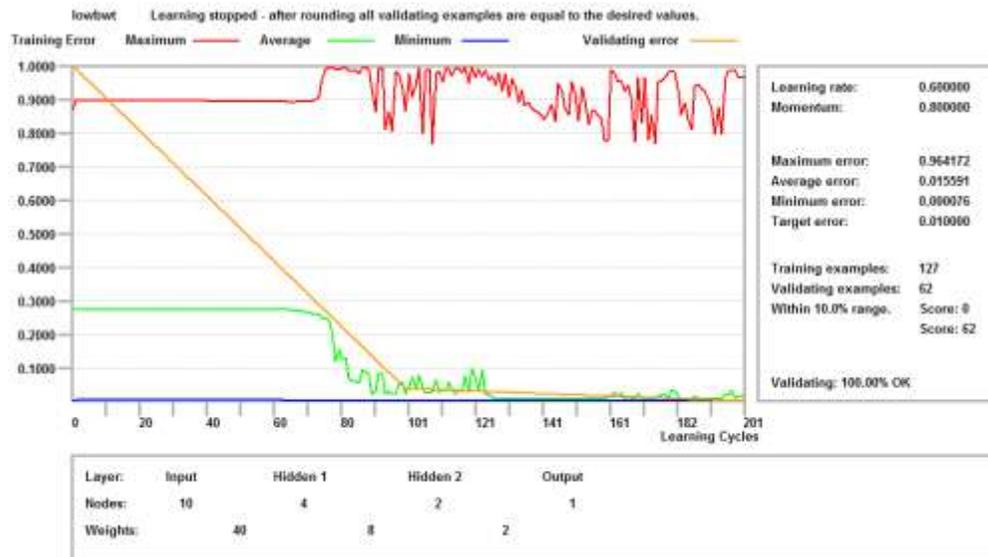


Figure 4: Shows the Training, error, and validation of the data set.

lowbwt 201 cycles. Target error 0.0100 Average training error 0.015591
 The first 10 of 10 Inputs in descending order.

Column	Input Name	Importance	Relative Importance
0	id	67.6277	
10	bwt	27.5960	
2	age	13.1022	
8	ui	8.1459	
6	ptl	7.1310	
5	smoke	4.7903	
7	ht	4.3548	
9	ftv	1.6945	
4	race	1.2488	
3	lwt	0.5646	

Figure 5: Most influential features in low birth dataset.

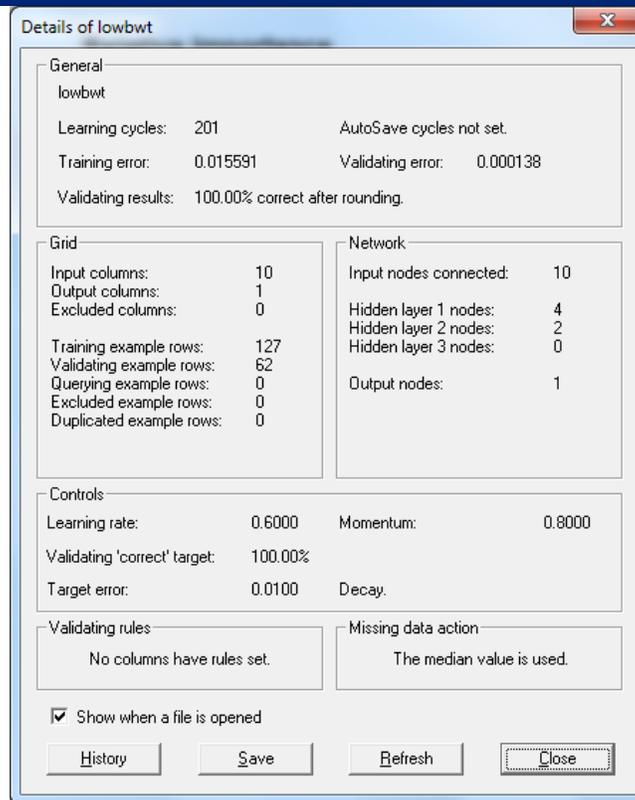


Figure 6: Details of the proposed ANN model

5. CONCLUSION

The artificial neural network model was presented to predict the weight of the newborn baby based on specific inputs. The model was tested and the total score was 100%. Thus, the potential of the artificial neural network to predict the weight of the newborn babies was reviewed.

References

1. "eMedicine - Extremely Low Birth Weight Infant : Article by KN Siva Subramanian, MD". Retrieved 2007-11-28.
2. Rizzo, Nicola; Simonazzi, Giuliana; Curti, Alessandra (2015-09-24). "Obstetrical risk factors of ELBW". *Italian Journal of Pediatrics*. 41 (Suppl 1): A35
3. "Labor and delivery - Low Birth Weight". Umm.edu. 2008-10-22. Retrieved 2020-01-05.
4. Tersigni, C. et al. (2014). "Celiac disease and reproductive disorders: meta-analysis of epidemiologic associations and potential pathogenic mechanisms". *Human Reproduction Update*. 20 (4): 582–593.
5. Saccone G, Berghella V, Sarno L, Maruotti GM, Cetin I, Greco L, Khashan AS, McCarthy F, Martinelli D, Fortunato F, Martinelli P (Oct 9, 2015). "Celiac disease and obstetric complications: a systematic review and metaanalysis". *Am J Obstet Gynecol*. 214 (2): 225–34.
6. Simhan HN, Caritis SN (2007). "Prevention of Preterm Delivery". *New England Journal of Medicine*. 357 (5): 477–487.
7. Knopik VS. Maternal smoking during pregnancy and child outcomes: real or spurious effect? *Dev Neuropsychol*. 2009;34(1):1-36.
8. Baraldi, A. and Parmiggiani, F. 1995. A neural network for unsupervised categorization of multivalued input patterns: an application to satellite image clustering.. *IEEE Transactions on Geoscience and Remote Sensing*, 33: 305–316.
9. Baret, F., Clevers, J. G. P. W. and Steven, M. D. 1995. The robustness of canopy gap fraction estimates from red and near-infrared reflectances: a comparison of approaches.. *Remote Sensing of Environment*, 54: 141–151.
10. Bastin, L. 1997. Comparison of fuzzy c- means classification, linear mixture modelling and MLC probabilities as tools for unmixing coarse pixels.. *International Journal of Remote Sensing*, 18: 3629–3648.
11. Baum, E. B. and Haussler, D. 1989. What size net gives valid generalization?. *Neural Computation*, 1: 151–160.
12. Benediktsson, J. A. and Sveinsson, J. R. 1997. Feature extraction for multisource data classification with artificial neural networks.. *International Journal of Remote Sensing*, 18: 727–740.

12. Benediktsson, J. A., Swain, P. H. and Ersoy, O. K. 1990. Neural network approaches versus statistical methods in classification of multisource remote sensing data.. *IEEE Transactions on Geoscience and Remote Sensing*, 28: 540–551.
13. Benediktsson, J. A., Swain, P. H. and Ersoy, O. K. 1993. Conjugate gradient neural networks in classification of multisource and very high dimensional remote sensing data.. *International Journal of Remote Sensing*, 14: 2883–2903.
14. Dash, P., Göttsche, F. M. and Olesen, F. S. 2002. Potential of MSG for surface temperature and emissivity estimation: considerations for real- time applications.. *International Journal of Remote Sensing*, 23: 4511–4518
15. alecri.github.io/downloads/data/lowbwt.csv
16. Just NN tool