IDENTIFYING MOST SUITABLE CLASSIFIER AND RISK FACTORS HIGHLY AFFECT ON LOW BIRTH WEIGHT IN DEVELOPING COUNTRIES: REVIEW

Abdullah Zahirzada [1], Mohmmad Akbar Shahpoor [2], Abdul Jalil Niazai [3]
[1] Department of Information Systems, Kunduz University, Afghanistan
[2] Department of Software Engineering, Kunduz University, Afghanistan
[3] Department of Software Engineering, Kunduz University, Afghanistan

ABSTRACT

Low birth weight (LBW) is a severe public health concern, especially in developing countries, and is often related to child morbidity and mortality. Identifying the essential factors that affect LBW is beneficial and a significant preventive step. It is also a good predictor of the infant's future health concerns. This research is concerned with identifying substantial risk factors for low birth weight and determining the best learning-machine classifier for LBW data. The study reveals that the most critical factors associated with LBW are the mother's age, education of the mother, sex of infants, preceding birth interval, Antenatal care visits (ANC), residence in rural areas, wealth status, and multiple births. Among several studies using machine learning/data mining approaches (i.e., Logistic Regression, Naive Bayes, Neural Networks, Random Forest, Decision Tree, Random Tree, K-Nearest Neighbor, J-48, and support vector machine), the Random Forest algorithm was shown to be the most suitable predictive modeling technique for LBW data.

Keywords: Developing countries, Low Birth Weight, Machine Learning, Classifier.

INTRODUCTION

The weight of newborns at birth is a good indicator of their immediate and long-term health. Low birth weight (LBW) is a significant public health concern and one of the leading causes of early newborn mortality and morbidity [1]. According to definition of the world health organization (WHO) new-born weight <2,500gr is called low birth weight (LBW), regardless of gestational age. This practical cut-off for worldwide comparison is based on epidemiological findings that newborns weighing less than 2,500gr are 20 times more likely to die than those considered normal [2]. Preterm delivery (birth before 37 weeks of pregnancy) or intrauterine growth restriction (IUGR) causes LBW. Preterm birth is the leading cause of LBW in industrialized nations, whereas IUGR is the leading cause in most underdeveloped countries [3,4].

The high neonatal mortality rates (NMR) in developing nations are primarily due to LBW, which increases morbidity and mortality in neonates [2]. The prevalence of LBW is 15.5% worldwide, and according to the WHO report, 96.5% of LBW newborns are born in developing countries [5]. Furthermore, it is a significant factor linked to increased infection risks, increased susceptibility to pediatric disease, reduced odds of child survival, long-term physical and mental impairments, and issues with behavior, learning, and psychosocial development during childhood [3]. LBW newborns face a high risk of death during the perinatal period, with nearly half of all neonatal fatalities being caused directly or indirectly by LBW [5]. Heart disease, diabetes, high blood pressure, behavioral disorders, intellectual and developmental disabilities, metabolic syndrome, obesity, cerebral palsy, blindness, deafness, psychological disorders, and a substantial risk of complications related to the stoma, including esophagus, stomach, duodenum, ileum, and colitis, may all affect newborn babies in the long run [3,6].

As a result, LBW is regarded as a global threat to underdeveloped countries, posing a barrier to child development [3]. Several different factors have been identified as drivers of LBW in previous studies, and it has been shown that eliminating these factors can help reduce early childhood morbidity and mortality [7]. Between 2012 and 2025, UNICEF-WHO established a 30% reduction in the LBW prevalence target. It has long been regarded as a public health issue to reduce LBW. The introduction of the Global Nutrition Goals in 2012 at the 65th World Health Assembly (WHA) [8], was a significant undertaking. Many children's lives would be saved if the target above goal could be met, and at present, it is still far from achieving this objective.

This research aims to examine the primary LBW risk variables in developing nations and discover the best predictive modeling algorithms for LBW data. This research will also assist researchers interested in conducting low birth weight studies in choosing an excellent predictive modeling technique. Second, our analysis aids policymakers in poor nations in formulating successful plans to strengthen communities, emphasizing a holistic approach to achieving their goals, particularly the Sustainable Development Goals-3 (SDG-3)

The aim of the study: Many studies have been conducted in terms of risk factors associated with LBW in developing countries. No one did any study to identify the factors that highly affect LBW in developing countries and determine which data mining techniques are the most suitable for LBW data in developing countries. This study tried to identify the attributes that highly affect LBW and finding the most appropriate predictive modeling algorithms for LBW data in targeted countries.

Material and Methods

A narrative assessment of health science literature about risk attributes related to LBW was undertaken utilizing machine learning/data mining approaches in developing nations. Bibliographic search, data systematization, article selection, primary analysis, evaluation, and final analysis were the stages of the research. Information was gathered in the first stage through metasearch engines and international journals such as IEEE, Jorjani, Springer, Journal of Basic Research in Medical Science, Maternal and Child Health Journal, Journal of Preventive Medicine & Public Health, etc. A direct bibliographical search was conducted in several chapters of specialized texts as a supplemental activity. The scope of the study was as follows:

Time frame: 2000 or recent.

Languages: English and Persian

Type of design: Data mining and machine learning techniques are used in descriptive investigations. Articles were gathered from research, reviews, and publications from the World Health Organization; after searching the databases, 50 possibly selected papers were found. Using the eligibility criteria provided, titles, abstracts, and complete texts were examined separately, except for 13 that did not correspond to the subject of interest. In addition, 14 papers were omitted because they did not address LBW risk factors. Finally, 23 publications were chosen, analyzed, and reviewed to achieve this literature review's goals, as shown in Figure 1.

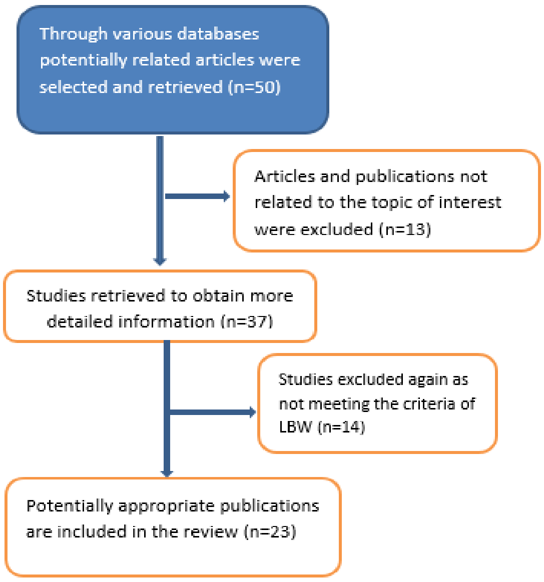

Figure 1. The selection process of the studies based on the data obtained in the study.

Results and Conclusion

This research review looked at a total of 23 papers. They revealed that developing countries account for 96% of LBW cases, and the total frequency of LBW in developing countries is 15.9%. Low Birth Weight was most common in Pakistan (35.1%), followed by Nepal (29.7%). This study found that the most significant risk factors associated with LBW in developing countries are mothers between the age of (35 to 49 years) who had a significantly greater risk of delivering LBW babies than younger mothers. Illiterate mothers (no formal education) also had a higher chance of providing LBW babies than educated mothers. Female babies were more prone to have an LBW than male babies.

Moreover, delayed conception (preceding birth interval) over 48 months had a significant relationship with LBW. The number of ANC visits was associated with substantial reductions in LBW, while receiving inadequate ANC was associated with an elevated risk of LBW. Mother's Nutrition is listed as the cause of LBW. Multiple births are also associated with preterm birth, which causes LBW. In most countries, a significantly increased risk of LBW in newborns is mothers with certain specific characteristics, such as low BMI, residence in rural communities, and lower wealth status of households compared to the wealthy groups. Table II reveals these attributes. Another finding of this study reveals that recent research has been conducted in some countries about LBW using machine learning/ data mining techniques such as (Naïve Bayes, K-Nearest Neighbor, Neural Networks, J-48, Logistic Regression, Random Forest, Decision Tree, Random Tree, and Support Vector Machine) Random Forest algorithm was the best approach in predicting and classification of low birth weight.

The previous studies revealed that most of the time, RandomForest produces better performance compared with other algorithms (i.e., classifiers); the benefits of Random Forest are it does not rely on the data, which is ideal for modeling high dimensional data, overcoming the issues of overfitting, removing prune trees. The most significant variable used for classification will be developed there; it runs efficiently and provides high predictive accuracy on massive datasets. If a large proportion of the data is missing, it is helpful to deal with missing values and outliers and preserve accuracy.

Table 1. The most significant risk factors highly affect LBW in developing countries.

No.	Features	Description
1	Maternal age	Age of the mother (years)
2	Antenatal care visits	No. of antenatal care visits (ANC)
3	PBI	The preceding birth interval
4	Infant gender	gender of infant (female or male)
5	Education	Education of the mother
6	Multiple births	The newborn baby is single, or twin born
7	Residence	Place of residence (rural areas)
8	Wealth status	The economic situation of the family

REFERENCES

1. Organization WH. International statistical classification of diseases and related health problems, tenth revision, 2nd ed. World Health Organization; 2004

2. Ikenna K Ndu1, Benedict O Edelu, Samuel N Uwaezuoke, Josephat C Chinawa, Agozie Ubesie, Christian C Ogoke, Kenechukwu K Iloh and Uchenna Ekwochi, Maternal Risk Factors Associated with Low-Birth-Weight Neonates: A Multi-Centre, Cross-Sectional Study in a Developing Country.

3. Rashidul Alam Mahumud, Marufa Sultana, Abdur Razzaque Sarker. distribution and determinants of Low Birth Weight in developing countries.

4. Michele *et. al*. 2001. Determinants of low birth weight among HIV-infected pregnant women in Tanzania

5. Tessa Wardlaw, Ann Blanc, Geneva; and Elisabeth Åhman, national regional and worwide estimates of low birth weight.

6. Low Birth Weight, children "s hospital of Philadelphia

7. Dasgupta A, Basu R. Determinants of low birth weight in a Block of Hooghly, West Bengal: a multivariate analysis. Int J Biol Med Res 2011;2(4):838-842.

8. World Health Organization. (2019). UNICEF-WHO low birthweight estimates: levels and trends 2000-2015 (No. WHO/NMH/NHD/19.21). World Health Organization

9. Yavar Naddaf, Mojdeh Jalali Heravi and Amit Satsangi., "Predicting Preterm Birth Based on Maternal and Fetal Data".

10. Rabindra Nath Das, Rajkumari Sanatombi Devi, Jinseog Kim, "Mothers' Lifestyle Characteristics Impact on Her Neonates' Low Birth Weight," International Journal of Women's Health and Reproduction Science Volume 2, No. 4, Summer 2014,pp.229–235.

11. Martina Mueller, Carol L. Wagner, David J. Annibale, Thomas C. Hulsey, Rebecca G. Knapp, and Jonas S. Almeida, "Predicting Extubation Outcome in Preterm Newborns: A Comparison of Neural Networks with Clinical Expertise and

Statistical Modeling," Pediatric Research, Volume. 56, No. 1, 2004, International Pediatric Research Foundation, pp. 11-18.
12. Guillermo Marshall, et al., "A New Score for Predicting Neonatal Very Low Birth Weight Mortality Risk in the NEOCOSUR South American Network," Journal of Perinatology, 25, 2005, pp.577-582.
13. Mahajan, and Praveen Kumar, "Predictors of Mortality and Major Morbidities in Extremely Low Birth Weight Neonates," Indian Pediatrics, Volume 50, December 15, 2013,pp.1119-1123.
14. Ghaderi ghahfarokhi, S., Sadeghifar, J., & Mozafari, M. (2018). A model to predict low birth Weight infants and affecting factors using data mining techniques. Journal of Basic Research in Medical Sciences, 5(3), 1-8.
15. Gupta, R. D., Swasey, K., Burrowes, V., Hashan, M. R., & Al Kibria, G. M. (2019). Factors associated with low birth weight in Afghanistan: a cross-sectional analysis of the demographic and Health survey 2015. BMJ Open, 9(5), e025715.
16. Hange, U., Selvaraj, R., Galani, M., & Letsholo, K. (2017, May). A Data-Mining Model for Predicting Low Birth Weight with a High AUC. In International Conference on Computer and Information Science (pp. 109-121). Springer, Cham.
17. Eliyati, N., Faruk, A., Kresnawati, E. S., & Arifieni, I. (2019, July). Support vector machines For the classification of low birth weight in Indonesia. In Journal of Physics: Conference Series (Vol. 1282, No. 1, p. 012010). IOP Publishing.
18. Yadav, H., Lee, N.: Maternal factors in predicting low birth weight babies. Med. J. Malays. 68 (1), 44–47 (2013)
19. Marshall, G., Tapia, J.L., Ivonne, D., Grandi, C., Barros, C., Alegria, A., Standen, J., Panizza, R., Bancalari, A., Lacarruba, J., Fabres, J.: A new score for predicting neonatal very low birth Weight mortality risk in the NEOCOSUR South American network. J. Perinatol. 25, 577–582 (2005)
20. Senthilkumar, D., Paulraj, S.: Prediction of low-birth-weight infants and its risk factors using Data mining techniques. In: Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management, pp. 186–194 (2015)
21. Desalegn, B.: Predicting Low Birth Weight Using Data Mining Techniques on Ethiopia Demographic and Health Survey Data Sets. Addis Ababa University (2011)
22. Ashdown-Lambert, J. R. (2005). A review of low birth weight: predictors, precursors, and Morbidity outcomes. The journal of the Royal Society for the Promotion of Health, 125(2), 7683.
24. A. Zahirzada and K. Lavangnananda, "Implementing Predictive Model for Low Birth Weight in Afghanistan," 2021 13th International Conference on Knowledge and Smart Technology (KST), 2021, pp. 67-72, DOI: 10.1109/KST51265.2021.9415792.