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Int. Conf. on Innovations in Science, Engineering and Technology (ICISET)
26-27 February 2022, Chittagong, Bangladesh
978-1-6654-8397-1/22/$31.00 ©2022 IEEE

Prediction of Weight Range of Neonate Using
Machine Learning Approach

Saleem Adeeba
Department of Computing and
Information Systems,
Sabaragamuwa University of Sri Lanka
Belihuloya, Sri Lanka
sadeeba@std.appsc.sab.ac.lk
Banujan Kuhaneswaran
Department of Computing and
Information Systems,
Sabaragamuwa University of Sri Lanka
Belihuloya, Sri Lanka
bhakuha@appsc.sab.ac.lk
B.T.G.S Kumara
Department of Computing and
Information Systems,
Sabaragamuwa University of Sri Lanka
Belihuloya, Sri Lanka
btgsk2000@gmail.com

Abstract— The weight of a neonate at birth is closely linked to mortality risk in the first year and developmental issues in infancy, and the chance of developing numerous diseases in adulthood. In epidemiological studies, birth weight is frequently considered the causal pathway to these health outcomes. Not all people have the facility to scan their fetus's weight before birth. In our research, we proposed a method to predict the weight class of the newborn baby by using existing data of pregnant women for the first six months. We identified 16 factors after an extreme literature review and expert opinion. Gradivity, age of pregnant woman, blood group, pregnant woman's employment, history of abortion, consanguinity, etc., are some of the factors identified. A dataset of 500 pregnant women was collected and preprocessed for applying the machine learning models. Once the preprocessing was done, the dataset was processed with Machine Learning (ML) models. After completion of data preparation, ML algorithms were used for the training and testing data set. This research utilized five ML algorithms to predict newborn baby weight at the six months of pregnancy. ANN and NB models have given accuracy above 70%, SVM and logistic regression algorithms provide accuracy above 60%, and Decision Tree provides accuracy below 60%.
Keywords—machine learning, newborn, neonate weight, ANN

I. INTRODUCTION

The shift from fetal to the neonate (also known as newborn), which occurs at delivery, is complicated and must occur swiftly to survive on its own [1]. The fetus prepares for the transition by creating hormones (cortisol, adrenaline, and thyroid hormones) that will spike at delivery, allowing the neonate to resume regular blood sugar, body temperature swiftly, and blood pressure levels [2, 3].

Baby birth weight is an important measurement to protect maternal and infant safety [4]. Agreeing to the World Health Organization (WHO), neonate weights between 3,000 g and 3,500 g are considered as average healthy baby birth weight, and baby weight of less than 2,500 g is assessed as Low Birth Weight (LBW), regardless of how far along the pregnancy was [5]. It signals a neonate's chances of being alive, growth, long-term health, and psychological development. Therefore, it's crucial to identify the factors that affect the baby's birth weight before pregnancy and until birth [6]. For example, based on the previously studied research, the factors that affect baby birth weight are commonly identified as genetics, parents' age, weight gains during pregnancy, length of gestation, gender of baby, number of babies, and so on [7, 8]. Further, according to the WHO recommendations, pregnancy weight gain with a good nutritional status is 10,000 g to 14,000 g (10 kg-14 kg) [9].

Tracking a baby's weight from birth is essential to ensuring healthy and growing normally [10]. Smaller babies have a higher risk of birth complications and a higher risk of having illnesses and other medical problems later in life [11]. LBW babies are also more probability of dying within the first twenty-eight days of their lives. That's why every country has a baby scale on maternity wards (and why health visitors always have them); a baby is weighed almost immediately after birth. Baby scales must be highly accurate to ensure that they deliver a dependable weight reading with pinpoint accuracy [12].

Predicting the baby's weight at the early stage undoubtedly determines the childbirth method appropriately [13]. It will be vital to identify risk factors that influence baby birth weight, such as (i) LBW, (ii) the higher the risk of infant mortality, (iii) labour complication, (iv) neonate survival, and (v) multiple birth complication [14]. Further, it will inform a baby's health in advance to the pregnant woman and medical practitioners, which will allow them to evaluate the nutrition level of the pregnant woman. More sophisticated techniques/equipment provide a way to predict the baby's birth weight [15, 16] in an appropriate, accurate, and standard manner. But these sophisticated equipment's are only used in developed countries. Developing countries like Sri Lanka lack enough cost, technology, resources, and trained workforce to use this equipment and are restricted to predicting the birth weight of every child [17].

A country like Sri Lanka manually maintains the pregnancy records details to inform the baby's health during pregnancy [18]. However, in developed countries, they use automated technology to predict the health and weight of the baby in advance that gives an accurate calculation [17]. Considering the issues and importance of the above study, there is a need for an alternative prediction technique to find the birth weight of every child in every country. Therefore, seeking a substitute method is easy to apply, with minimum cost and enough resources. However, the baby birth weight prediction cannot be made directly, and it follows rough estimation with some association factors [19] before pregnancy, the pregnancy, until birth. It includes a pregnant woman's weight, height, age, haemoglobin level, sugar level during pregnancy, etc. [20]. This research paper identifies an alternative prediction method of baby birth weight class for every child with the minimum cost at the pregnancy stage at six months. Thus, a baby weighing less than 3,200 g is considered one class, and a baby weighing greater than or equal to 3,200 g is regarded as another class.

2022 International Conference on Innovations in Science, Engineering and Technology (ICISET) |
978-1-6654-8397-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICISET54810.2022.9775840

Machine Learning (ML) is a study of computer algorithms that can learn and develop on their own with experience and data. It’s often seen as part of artificial intelligence. ML models apply sample data to create models that can make forecasts without being definitively programmed. Globally, it’s used in broad fields. Such as health, education, agriculture, Information technology, and so on [21].

The main objective of this paper is to utilize ML technologies to predict the baby birth weight class with minimum errors at the end of 6 months. This research paper proposes a baby’s birth weight prediction model based on ML algorithms. The model trained with a different 16 factors (attributes) that affect the baby's birth weight. Such as pregnant woman’s BMI, pregnant woman’s age, and haemoglobin levels are some of them.

II. LITERATURE REVIEW AND RELATED WORKS

A baby's birth weight is the first thing practitioners consider while the pregnant woman delivers the baby. However, all baby’s birth weight is not predefined; it will vary for each neonate. Knowing a baby's weight is a clear indicator of the baby’s health. Therefore, knowing the factors affecting a baby’s birth weight consideration is a must.

The UK MARSDEN article discusses that the factors affecting baby weights are (i) genetics (ii) age of pregnant woman (iii) number of children (iv) length of pregnancy (v) pregnant woman’s birth baby weight (vi) diet during gestation (vi) pregnant woman’s practice (viii) gender of the baby (ix) parent’s medical condition and (x) ethnicity [7].

Moreover, the Healthgrades article discusses affecting factors such as blood pressure, diabetes, heart diseases, asthma, kidney disease, lupus, anaemia, and dental health [12]. Also, previous studies were carried out in different countries regarding the components impacting the neonate’s weight.

According to Chandra S. Metgud, Vijaya A. Naik, and Maheshwar D. Mallapur finds, factors impacting baby weight include illiteracy among pregnant women, passive smoking exposure, childbearing later in life, shorter intervals between pregnancies, pre low weight kids, the weight of pregnant women, growth of weight, pregnancy-induced hypertension, pregnancy with a significant risk of complications, and antenatal registration beyond the due date. It was carried out in India, Rural Karnataka [8].

One of the publications had been carried out by students in London discussed the most influencing factors for affecting birth baby weight was mentioned as smoking, maternal height and parity, gestation, and the baby's sex [22]. Further, Talie, et al. [23] discusses that infant sex, anaemia during pregnancy, history of LBW, pregnant woman's employment, and so on are the factors affecting the birth baby weight, it was carried out in Debre Markos Referral Hospital, Northwest Ethiopia [5, 23].

As the literature results mentioned above indicate, a baby's birth weight is influenced by several factors. Some factors may vary from one country to another. Further, the above literature primarily focuses on the reasons for the LBW. As a common understanding, similar influencing factors in each country are mentioned as pregnancy weight, height, age, gender of the baby, and maternal weight.

Based on the previous studies and concerns from medical practitioners, this research paper identifies the following 16 factors that affect the baby weight used to predict the baby weight at the six months, such as gravidity, age of pregnant woman, blood group of a pregnant woman, pregnant woman's employment, history of abortion, consanguinity, pre-pregnancy scanning done, history of subfertility, height, weight, and BMI of pregnant woman, haemoglobin level, blood sugar, tracking of the weight of pregnant woman until first six months pregnancy, fundal height, and gender of the baby.

ML is an essential technology for the healthcare sector. Thus, it is being used in many aspects of health care, including the invention of emerging health treatments, patient data and information management, and chronic illness therapy. According to the New Yorker, computer scientist Sebastian Thrum: "Machines will make the human brain 1,000 times more powerful, just as they made human muscles 1,000 times stronger" [21, 24].

For example, illnesses and therapies are predicted, health risks are forecasted for distinct demographics of people, assist in the management of medical records and workflow, distinguishes between malignancies and normal anatomy, drug development is aided and expenditures are reduced, identify potential clinical trial sites, identifies healthcare gaps and assists pathologists in making more accurate and timely diagnoses, etc. These are some examples that can be achieved using ML algorithms [21, 24]. Above mentioned studies have given the importance of ML and ML in healthcare. Therefore, this research paper identifies the ML algorithms to predict birth weight at six months of pregnancy.

Karthiga, et al. [25] used TensorFlow ML algorithms to predict the newborn's birth weight. It's emphasized on creating an online application that forecasts newborn weight based on the gender of the baby, the number of siblings, length of pregnancy, and age. Tao, et al. [26] focused on fetal birth weight prediction with measured data using temporal ML. By merging multiple e-medical data with the B-ultrasonic monitoring of pregnant women, this research aims to develop a hybrid birth weight prediction classifier using long short-term memory (LSTM) networks.

Hussain and Borah [27] had predicted the baby weight based on the different types of features of the pregnant woman. In this study, the newborn baby's birth weight prediction was carried out using two ML techniques said Gaussian NB and Random Forest.

As a result of the literature mentioned above, it has the drawback of the prediction period of the baby weight. Thus, the prediction period of the baby's weight is not mentioned. But this research paper fills the gap by predicting the baby weight of the six months of the pregnancy. Predicting birth weight at six months before the baby is born is the most effective strategy to ensure that the neonate receives special attention as soon as feasible. It assists us in making arrangements for doctors and specific facilities before the birth of the kid.

Table I shows the comparison of the existing studies in the context of number of attributes, technologies (algorithms) used for prediction and prediction month of the birth weight.

TABLE I. COMPARISON OF THE EXISTING STUDIES

Paper	# of attributes	Some attributes names	Technologies used	Prediction month of the birth weight
[25]	7	Weight in pounds, Development weeks, majority etc.	ML (TensorFlow) library	Not mentioned or after completion of gestational weeks
[26]	6	Height, Age, Abdominal Circumference of Pregnant Women etc.	LSTM	Not mentioned or after completion of gestational weeks
[27]	18	Age, Height, Blood Group of mothers etc.	Gaussian NB and Random Forest	Not mentioned or after completion of gestational weeks
[28]	9	Smoking, Race, Maternal-Age, Weight etc.	ANN	Not mentioned or after completion of

gestational weeks
This
research
16
Gravidity, Age, Blood group,
Height etc.
SVM, ANN, NB, Decision Tree,
and Logistic Regression
At six months of period

III. PROPOSED APPROACH

Fig 1 shows the methodology graph for baby weight prediction using ML algorithms at six months of pregnancy.

A. Attributes selection:

Several interviews were conducted with experts, and along with the help of experts' comments and from the extreme literature survey, 16 factors were identified that affect the neonate weight. Thus, gravidity, age of pregnant woman, blood group, pregnant woman's employment, history of abortion, consanguinity, pre-pregnancy scanning, history of subfertility, the height of pregnant woman, weight of pregnant woman, BMI of pregnant woman, haemoglobin level, blood sugar, the weight of pregnant woman until six months pregnancy, fundal height and gender of the baby.

B. Data collection:

When a woman begins her pregnancy in Sri Lanka, she is registered for antenatal care, and two sets of records are kept: "A" card and "B" card. During a prenatal clinic appointment, pregnant women hold the "A" card in their hands and display it to health care staff. Midwives keep track of the "B" for record-keeping. Both 500 "A" cards and "B" cards were collected from different MOH divisions areas from Sri Lanka during this study. Record card keeps several records in their sheet. Such as the name of the pregnant woman, age, employments of both wife and husband, BMI, blood group of a pregnant woman, and so on.

Selected 16 attributes were extracted from both A and B cards and manually entered. At last baby's birth baby weight grouped into two classes. Baby weight less than 3,200g is considered one class, and baby weight greater than or equal to 3,200g is regarded as another class.

Further, from the concerns from the medical practitioners, some factors affecting baby weight are grouped into classes according to their problems. Such as, normal BMI should be from 18.5 to 25, average haemoglobin level for pregnant women is 12 to 16, below 12 it's considered as iron deficiency, and below 10 considering as anaemia, regular fasting blood sugar for the pregnant woman is from 90 to 100, and correct age of having pregnancy is 20 to 35. Table II indicates the attributes and the relevant description during data collection of the pregnant woman.

Fig. 1. Proposed Approach

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TABLE II. IDENTIFIED ATTRIBUTES AND THE RELEVANT DESCRIPTION
No Attribute Description Representation Levels/unique values
1. Gravidity
Gravidity is defined as the number of times a
woman has been pregnant.
Integer
E.g., 3 (The pregnant woman has already
given birth to 2 children)
2. Age The current age of the pregnant woman Range
0: <20
1: 20-35
2: >35
3. Blood group The blood group of the pregnant woman Varchar A+,A-,B+,B-,O+,O-,AB+,AB-
4.
Employment
pregnant woman
During pregnancy, she worked or not Scale
0: Unemployed
1: Employed
5. History of abortion
The pregnant woman experienced with
abortion or not
Range
0: Not Aborted
1: Aborted
6. Consanguinity
Malformations at birth, growth of the mind,
sickness, and humanity are linked to
consanguinity, which can be said as a blood
relation's marriage or union.
Scale
0:Non Consanguinity
1: Consanguinity
7.
Pre-pregnancy
scanning
The pregnant woman pre-scanned or not Factors
2 level, 0 for not pre-scanned, 1 for pre-
scanned
8.
History of
subfertility
Pregnant woman experience in late
pregnancy or not through her history since
the marriage
Scale
0: Non-late pregnancy
1: Late pregnancy
9. Height Height of pregnant woman before pregnancy Float in meters E.g., 1.52 m
10. Weight Weight of pregnant woman before pregnancy Float in kilograms E.g.: 52.5 kg
11. BMI
BMI of the pregnant woman before
pregnancy
Range
23.3, three levels, 0 for below 18.5, 1 for
between 18.5 to 25, and 2 for above 25
12. Haemoglobin level
Haemoglobin level at the beginning and

middle of pregnancy
Range
11.1, 3 levels, 0 for below 10, 1 for 10-12, 2
for above 12
13. Blood sugar
Blood sugar at the beginning and middle of
pregnancy
Range
0: <90
1: 90-100
2: >100
14.
Weight of pregnant
woman from 1 – 6
months
The weight measures pregnant women until
the first six months
Float in kilograms E.g.: 52.5 kg
15. Fundal Height
Distance from the pubic bone to the uterus's
top
Integer in centimeter E.g., 20 cm
16. Gender of the baby Gender of the newborn baby Varchar Girl or Boy

C. Data preprocessing

Data preprocessing transforms raw data into usable information, then fed into the training model for accurate medical decisions, diagnoses, predictions, and treatments [24].

The data collection set consists of both discrete and continuous variables. In case the uniformity of the values is maintained in the data set. Some attributes have textual format thought the data set. Such as blood group and gender. Therefore, those textual datasets are categorized into groups, and groups are labelled in a numeric way using the scikit-learn library. It’s one of the ML libraries for python programming. Further, the collection of data set included nan/blank values. In case those nan values changed into numeric values using the NumPy library.

D. Data preparation

Part of analyzing ML involves splitting data into training and testing sets. Once data sets were divided into two groups, the training set was allocated with the majority (80%) of data. On the other hand, other testing sets received a lesser (20%) portion of data. Analysis Services takes a random sample of the data to guarantee that the training and testing sets are comparable. We can decrease the effects of data discrepancies and better understand the model's properties by utilizing the same amount of data for training and testing.

After preprocessing was carried out, the data set was split into training and testing using the ski learn library. In data preparation training data set is trained to apply the ML algorithms in advance.

E. Implementation of ML models

After completion of data preparation, ML algorithms were used for the training and testing data set. In this research, five ML algorithms were used to predict newborn baby weight at the six months of pregnancy.

Construction of ANN model: The ANN approach design consists of four layers. Thus, input layer, first hidden layer, second hidden layer, and output layer. The following Table III shows the configuration for the neural network.

TABLE III. CONFIGURATION FOR THE NEURAL NETWORK MODEL

Parameter	Value
Epochs	50
Batch size	32
Optimizer	Adam
Loss	Binary_crossentropy
Activation (first hidden layer)	ReLu
Activation (second hidden layer)	ReLu
Activation (output layer)	Sigmoid

Construction of SVM: SVM is one of the supervised learning algorithms used for classification and regression problems. In this approach, SVM kernel 'RBF' is used for training and testing the data set. Further, Logistic Regression, NB, and Decision Tree are applied to the training and testing data set.

IV. RESULTS AND DISCUSSION

The research was performed on Windows operating system with Intel(R) Core (TM) i7-8550U CPU @ 1.80GHz 1.99 GHz and 8 GB RAM computer. Python programming

language implements preprocessing and the five different ML algorithms. Factors are collected from maternal "A" and "B" records and manually entered into the system. The baby weight data set is classified into two classes to train the ML model.

A. Data Preprocessing

Data preprocessing is a process to get the useable information to train the data set for the ML model, which was, explained in detail in the previous section. For example, before the preprocessing, the data shows gender as boy and girl. But after its preprocessing, it's shown as 0 and 1. This is also applicable to the factor of the blood group of pregnant women.

B. Performance of ML models

To compute the model error, the ANN uses a loss function technique. It's a technique for altering the weights and biases of data input. The optimization procedure updates the weight parameters to decrease the loss function and determine the model error. Fig 2 depicts the model train by epoch.

Fig. 2. Model train by epoch

The signal processing community developed the Receiver Operating Characteristics (ROC) curve to assess a human operator's ability to differentiate informative radar signals from background noise. It was then primarily utilized in the medical decision-making community to evaluate the utility of a diagnostic test. The trade between the true positive rate and the false-positive rate for a predictive model utilizing different probability thresholds is summarized by ROC Curves. Thus, the following equations explain the true positive and false

positive rates in more detail.
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(1)
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›
B
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B

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(2)

The model's efficiency is judged by measurement precision. The most important criterion for model evaluation is accuracy. The number of tuples correctly classified based on the formula is accuracy. The following formula explains the accuracy in detail.

2Đ
à
ñ
ñ ! !1
(3)

Fig 3 shows the accuracy of the final ANN model for the training and testing dataset.

Fig. 3. Accuracy of the final ANN model for the training and testing dataset

Further, we use recall, F1 score, precision to evaluate each model using five algorithms. The recall is the method of correctly identifying the true positives. The following formula gives it.

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A}
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(4)

Simply precision is defined as the ratio between true positives and all the positives, and the following formula defines it.

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ñ
ñ !
(5)

F1 score is a function of precision and recall, and it can be defined in the following formula.

1 rB
!""" $ %&%'()
!"" $ %&%'()
(6)

As from the equations mentioned above, TP indicates true positive, TN indicates true negative, FP indicates false positive, and FN indicates false negative. In this research, TP mentions that if the predicted class is 1, real results are also 1. TN mentions that if the predicted class is 0, real results are also 0. FN mention as, if predicted class 0, but real results is 1. Table IV summarizes each model's recall, precision, and F1 score. Further, Fig 4 shows the comparison of models with percentage accuracy.

TABLE IV. RECALL, PRECISION, AND F1 SCORE FOR EACH OF THE IMPLEMENTED MODEL

	Recall %	Precision %	F1 score%
ANN	73.97	72.97	73.46
SVM	67.74	60.00	63.63
NB	74.19	65.71	69.69
Logistic Regression	65.51	54.28	59.37
Decision Tree	54.54	51.42	52.94

Fig. 4. Accuracy of each model

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V. CONCLUSION AND FUTURE WORK

This research paper identifies the process to predict the newborn baby's weight at six months of pregnancy using ML algorithms. Five different machine algorithms are used for trained data to check the effectiveness of prediction mechanisms. In conclusion, ANN and NB models have given accuracy above 70%, SVM and logistic regression algorithms provide accuracy above 60%, and Decision Tree provides accuracy below 60%.

The future work of this research can be improved in many ways. We planned to increase the baby weight class to get a more accurate prediction. Also, we are planning to predict the appropriate delivery method for a pregnant woman. Further, we are planning to increase the attribute set too.

ACKNOWLEDGEMENT

The authors would like to thank the MOH division and medical practitioners in Sri Lanka for their valuable advice and support in collecting information on the post-pregnant woman.

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Ranjbar et al. BMC Pregnancy and Childbirth (2023) 23:803 https://doi.org/10.1186/s12884-023-06128-w RESEARCH Machine learning-based approach for predicting *low* birth weight Amene Ranjbar 1 , Farideh Montazeri 2 , Mohammadsadegh Vahidi Farashah 3 , Vahid Mehrnoush 2 , Fatemeh Darsareh 2* and Nasibeh Roozbeh 2 Abstract Background Low birth weight (LBW) has been linked to infant mortality. Predicting LBW is a valuable preventative tool and predictor of newborn health risks. The current study employed a machine learning model to predict LBW. Methods This study implemented predictive LBW models *based* on the data obtained from the “Iranian Mater- nal and Neonatal Network (IMaN Net)” from January 2020 to January 2022. Women with singleton pregnancies above the gestational age of 24 weeks were included. Exclusion criteria included multiple pregnancies and fetal anomalies. A predictive model was built using eight statistical learning models (logistic regression, decision tree classification, random forest classification, deep learning feedforward, extreme gradient boost model, light gradi- ent boost model, support vector machine, and permutation feature classification with k-nearest neighbors). Expert opinion and prior observational cohorts *were* used to select candidate LBW predictors for all models. The area under the receiver operating characteristic curve (AUROC), accuracy, precision, recall, and F1 score were measured to evaluate their diagnostic performance. Results We found 1280 women with a recorded LBW out of 8853 deliveries, for a frequency of 14.5%. Deep learning (AUROC: 0.86), random forest classification (AUROC: 0.79), and extreme gradient boost classification (AUROC: 0.79) all have higher AUROC and perform better than others. When the other performance parameters of the models men- tioned above with higher AUROC were compared, the extreme gradient boost model was the best model to predict LBW with an accuracy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. *According* to the feature impor- tance rank, gestational age and prior history of LBW were the top critical predictors. Conclusions Although this study found that the extreme gradient boost model performed well in predicting LBW, more research is needed to make a better conclusion on the performance *of* ML models in predicting LBW. Keywords Low birth weight, Fetal weight, Birth weight, Machine learning, X gradient boost model Background Birth weights less than 2500 g are called *low* birth weight (LBW). LBW has been linked to infant mortality and its consequences [1]. Predicting LBW is thus a valuable pre - ventative tool and predictor of newborn health risks. Pre- vious research has found that maternal demographics, preexisting health conditions, and prenatal care level are all linked to LBW [2, 3]. Thus, pinpointing which preg -

nant patients are most likely to have a baby with LBW during the preconception or early pregnancy stages is Open Access BMC Pregnancy and Childbirth *Correspondence: Fatemeh Darsareh famadarsareh@yahoo.com 1 Fertility and Infertility Research Center, Hormozgan University of Medical Sciences, Bandar Abbas, Iran 2 Mother and Child Welfare Research Center, Hormozgan University of Medical Sciences, Bandar Abbas, Iran 3 Amirkabir University of Technology, Tehran, Iran critical for saving neonatal lives and reducing potentially avoidable medical costs through direct clinical and health policy interventions. There are some documented stud - ies on using ML in perinatal care and maternal health. Previous LBW prediction studies achieved good perfor - mance in predicting LBW; however, all previous studies recommended more studies due to study limitations such as small sample size or limited feature selection [4–7]. *In* this study, we aimed *to* evaluate the performance of eight different *ML* algorithms in predicting LBW. Methods The findings of this retrospective cohort study are based on birth records obtained from the "Iranian Maternal and Neonatal Network (IMaN Net)," a legitimate national system, from January 2020 to January 2022. IMaN Net is a comprehensive system for registering maternal and newborn *information* on the outcomes of each delivery, which is completed daily by midwives in all birth centers and hospitals throughout Iran in an integrated manner. All patients' personal information was deidentified and not disclosed. Women with singleton pregnancies above the ges - tational age of 24 weeks who gave birth during a study period were included. The target population in this study was divided into LBW ("d 2499 g) and not LBW ("e 2500 g), which is the national standard definition [8]. Exclu - sion criteria included multiple pregnancies and fetal anomalies. A predictive model was built using eight statistical learning models, including logistic regression, decision tree classification, random forest classification, deep learning feedforward, extreme gradient boost classifi - cation (XGBoost), light gradient boost (LGB), support vector machine (SVM), and permutation feature clas - sification with k-nearest neighbors (KNN). Expert opin- ion and prior observational cohorts *were* used to select candidate LBW predictors for all models [9, 10]. Pre - dictor factors included maternal age, educational level, maternal occupation, place of residence, inadequate prenatal care (less than three prenatal care visits), smok - ing, drug addiction, maternal anemia, cardiovascular dis- ease, chronic hypertension, hepatitis, COVID-19, overt diabetes, gestational diabetes and thyroid dysfunction, parity, preeclampsia, fetal gender, method of childbirth, previous *history* of LBW, supplementary and vitamins intake were obtained from patient medical records. We used Chi-square test *to* evaluate the association between predicting factors mentioned above and LBW. Then we performed ML analysis approach. We followed the Guidelines for Developing and Reporting Machine Learning Predictive Models in Biomedical Research: A Multidisciplinary View to report our findings. The programming language Python was chosen to create *the* machine learning model. Scikit-learn was used to imple - ment the ML algorithm. Scikit-learn is a machine-learn- ing library written in Python. It includes an extensive collection of cutting-edge machine-learning algorithms for both supervised (including the multi-output classifi - cation and regression algorithm) and unsupervised prob- lems [11]. Internal validation *was* carried out *with* *the* help of k-fold cross-validation. The cases were randomly assigned to either the "training set" (70%) or the "test set" (30%) using a random number generator. The origi - nal dataset kept the rate of LBW and non-LBW groups in *the* training and test sets constant. Using the training set, we arranged the parameters *of* the prediction models and evaluated their performance using the "test set". The average performance was calculated by repeating these ten times. Metrics, including area under the receiver operat - ing characteristic curve (AUROC), accuracy, precision, recall, and F1 score, *were* used to assess the predic - tive power of the models. The accuracy metric calcu- lates how often a model is correctly predicted across the entire dataset. Precision measures how many of the model's "positive" predictions were correct. The model's recall estimates how many positive class samples in the dataset were correctly identified. The F1 score combines precision and recall by using their harmonic mean, and maximizing the F1 score implies maximizing both preci - sion and recall simultaneously. As a result, researchers have chosen the F1 score to evaluate their models in con - junction with accuracy. We used AUROC as the primary performance metric because it is a widely used index to describe the ML model's ability to predict outcomes. The metrics were scaled from 0 to 1, with higher values indi - cating a better model [12]. Results Of 8850 eligible cases, we found 1280 women with a recorded LBW, for a frequency of 14.5%. The demo - graphic and clinical characteristics of study population is given in Table 1. As it shown, maternal age, living residency, gestational age, parity, access to prenatal care, maternal anemia, chronic hypertension, preeclampsia, drug addiction, COVID-19, previous LBW, and newborn gender was linked to LBW. *In* this study, we attempt to evaluate parameters and feature selection based on performance parameters using various ML algorithms. A plot ROC chart, as shown in Fig. 1, and calculate AUROC as a plot that allows the user to visualize the tradeoff between the classifier's sensitiv - ity. Deep learning (AUROC: 0.86), random forest clas- sification (AUROC: 0.79), and XGBoost classification Page 3 of 7 Ranjbar et al. BMC Pregnancy and Childbirth (2023) 23:803 (AUROC: 0.79) all have higher ROC_AUC and perform better than others, as shown in Fig. 1. Other performance parameters for each algorithm are shown in Table 2. Other performance parameters indi - cate that the XGBoost classification performs more than all. Random forest classification and deep learning feed - forward are also very close. When the accuracy, preci- sion, recall, and F1 score of the models mentioned above with higher AUROC were compared, the XGBoost model was the best model to predict LBW with an accuracy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. The confusion matrix of the XGBoost classification model is shown in Fig. 2. Figure 3 presents an analysis of *the* importance of vari - ables in the XGBoost algorithm. As the feature impor- tance rank was identified, gestational age and previous history of LBW were the top critical predictors. Discussion With the exponential growth in the quantity and dimen- sion of healthcare data in recent years, ML approaches for dealing with complex and high-dimensional data have been introduced [13–15]. *In* this study, we aimed to eval - uate the performance of eight different *ML* algorithms in predicting LBW. According to our findings, the XGBoost classification model had a more significant diagnostic performance parameter with an AUROC of 0.79, accu - racy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. XGBoost classification is a supervised machine learning algorithm based on a distributed gradient- boosted decision tree [16]. It can produce consistent Table 1 Demographic and clinical factors associated with *low* birth weight OutcomeNon-LBW (n = 7570)LBW (n = 1280)P-value Maternal age < 0.001 13–19137 (1.8)36 (2.8) 20–356247 (82.5)995 (77.7) Above 351186 (15.7)249 (19.5) Education0.348 Illiterate480 (6.3)73 (5.7) Primary2344 (31.0)378 (29.5) High-school/ Diploma 3463 (45.8)609 (47.6) Advanced1283 (16.9)220 (17.2) Occupation0.299 Housewife6798 (89.8)1146 (89.5) Worker/employee772 (10.2)134 (10.5) Living residency0.045 Urban5056 (66.8)823 (64.3) Rural2517 (33.2)457 (35.7) Gestational age < 0.001 24–36 +6 429 (5.7)801 (62.6) 37–417141 (94.3)479 (37.4) Parity < 0.001 Primiparous2056 (27.1)439 (34.3) Multiparous5517 (72.9)841 (65.7) Access to prenatal care 0.030 Yes7343 (97.0)1255 (98.0) No230 (3.0)25 (0.2) Maternal anemia0.047 No7364 (97.2)1233 (96.3) Yes209 (2.8)47 (3.7) Chronic hyperten- sion 0.005 No7501 (99.0)1256 (98.1) Yes72 (1.0)24 (1.9) Cardiovascular disease 0.803 No7492 (98.9)1267 (99.0) Yes81 (1.1)13 (1.0) Diabetes0.276 No6420 (84.8)1094 (85.5) Yes1153 (15.2)186 (14.5) Preeclampsia < 0.001 No7196 (95.0)1083 (84.6) Yes377 (5.0)197 (15.4) Drug addiction < 0.001 No7530 (99.4)1251 (97.7) Yes42 (0.6)29 (2.3) Previous *low* birth weight < 0.001 No7479 (98.8)1089 (85.1) Yes94 (1.2)191 (14.9) Data are presented as n (%) Table 1 (continued) OutcomeNon-LBW (n = 7570)LBW (n = 1280)P-value COVID-190.020 No7465 (98.6)1250 (97.7) Yes108 (1.4)30 (2.3) Thyroid dysfunction0.999 No6778 (89.5)1146 (89.5) Yes795 (10.5)134 (10.5) Hepatitis0.079 No7543 (99.6)1279 (99.1) Yes30 (0.4)1 (0.1) Newborn gender < 0.001 Male3942 (52.1)599 (46.8) Female3631 (47.9)681 (53.2) Supplementary intake 0.078 No4 (0.1)5 (0.4) Yes7569 (99.9)1275 (99.6) Page 4 of 7 Ranjbar et al. BMC Pregnancy and Childbirth (2023) 23:803 results while minimizing overfitting by employing a par- allel tree-boosting strategy. Furthermore, XGBoost can use the importance score to determine *the* importance of each feature. Previous studies evaluating different ML machines for predicting LBW will also have prom - ising results. According to Ahmadi et al., the random forest model performed well in terms of diagnostic per - formance, with an accuracy of 0.95, recall of 0.72, and AUROC of 0.89 [5]. Another study by Desiani et al. found that naive Bayes had excellent diagnostic performance, with an accuracy of 0.85 and a recall of 0.72 [17]. How - ever, both studies were limited by a small sample size (less than 1000 participants). Recent studies with larger sample sizes also demon - strated good performance. For example, in a survey by Eliyati et al., with a sample size of 12,500 study par - ticipants, SVM showed high diagnostic performance in predicting LBW with an accuracy of 0.93 [18]. Ren et al. used a more extensive study in this field, with a sample size of 266,687 birth records over six years. According to their findings, the XGBoost classification model had the highest recall score of 0.85, but the AUROC score was only 0.61 [19]. Although our study did not have the largest sample size of any study in this field, we believe that using hos - pital records made our feature selection rich enough to make a reasonable conclusion on identifying LBW risk factors. In our study, we surveyed maternal age, edu - cational level, place of residence, inadequate prenatal care (fewer than three prenatal care visits), drug addic - tion, maternal anemia, cardiovascular disease, chronic hypertension, pyelonephritis, hepatitis, COVID-19, overt diabetes, gestational diabetes and thyroid dysfunction, parity, preeclampsia, and history of LBW. Among all the potential predisposing factors of LBW, gestational age and previous history of LBW were the top critical predictors. In line with previous findings [20, 21], ges - tational age is the highest predictor of LBW. Being born too soon (premature birth) *is* the most common cause of LBW. The prior history of LBW was another weighted factor in predicting LBW. It has been reported that *the* risk of LBW recurs between pregnancies. Women with a Fig. 1 AUROC *of* ML models Table 2 Performance parameters *of* models with the highest AUROC RowAlgorithmsAccuracyPrecisionRecallF_1 Score 1Random Forest

Classification0.780.850.700.77 2XGBoost Classification0.790.870.690.77 3Deep Learning- Feed Forward0.780.840.700.76 Page 5 of 7 Ranjbar et al. BMC Pregnancy and Childbirth (2023) 23:803 Fig. 2 XGBoost classification confusion matrix Fig. 3 Feature *importance* of the XGBoost classification in the prediction *of* *low* birth weight Page 6 of 7 Ranjbar et al. BMC Pregnancy and Childbirth (2023) 23:803 previous LBW baby have been identified as potential car- riers of the recurrent risk and *have* a higher recurrence risk of LBW in their subsequent pregnancy than those with a previous normal birth weight baby [22]. Other fac - tors, such as maternal comorbidities, sociodemographic characteristics, and fetal gender, were not among the weighted factors in predicting LBW, in contrast to pre - vious studies. In one study, Bekele et al. found that fetal gender, marriage to birth interval, mother's occupation, and mother's age were all weighted factors in predicting LBW [23]. Another study found that maternal pre-preg - nancy weight, mother's age, number of doctor visits dur- ing the first trimester, and previous preterm labor were the most significant risk factors for LBW [4]. The dif - ferences in findings could be attributed to study design, the type *of* ML models used, geographical differences, or imbalances in each study's dataset. It should be noted, however, that clinicians can use the key findings of each study to identify high-risk pregnant patients early in their pregnancy using early prenatal care screening tools. Although we used a large dataset with a lot of maternal and neonatal information, a significant variable, like body mass index, was missing in most *of* the birth records, so we couldn't use this factor in our selection features, which is a significant limitation of the study. Conclusion Using ML approaches to predict LBW yielded promising results. As a result, this study might add to the current perinatal care literature. Although this study found that the XGBoost model performed well in predicting LBW, more research is needed to make a better conclusion on the performance *of* ML models in predicting LBW. Abbreviations LBW Low birth weight ML Machine learning XGBoost Extreme gradient boost LGB Light gradient boost SVM Support vector machine KNN K-nearest neighbors Acknowledgements All of the authors acknowledged Hormozgan University of Medical Sciences. Authors' contributions F.D. and N.R. wrote the proposal. F.M. and V.M. contributed significantly to data collection. The findings were analyzed and interpreted by M.F. F.D., the primary contributor to the manuscript's commenting and editing. A.R. assessed the manuscript's scientific content critically. The final manuscript for submission was read and approved by all authors. Funding None. Availability of data and materials The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. Declarations Ethics approval and consent to participate This study complied with the Declaration of Helsinki and was performed according to ethics committee approval. The Ethics and Research Committee of the Hormozgan University of Medical Sciences approved the study. The records of all patients who provided informed consent for using their data for research purposes were analyzed. For those under the age of 18 the informed consent was taken from their gurdian. Statistical analysis was performed with patient anonymity following ethics committee regulations. Consent for publication Not applicable. Competing interests The authors declare no competing interests. Received: 16 August 2023 Accepted: 14 November 2023
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