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Fetal Birth Weight Estimation with Machine Learning Techniques in 15-40 Weeks of Pregnancy

Özlem Dülger[1], Ahmet Dursun[2], Usame Ömer Osmanoğlu[3]

[1]*Karamanoğlu Mehmetbey University, Faculty of Medicine, Department of Obstetrics and Gyneacology, Karaman, Türkiye*
[2]*Karamanoğlu Mehmetbey University, Faculty of Medicine, Department of Anatomy, Karaman, Türkiye*
[3]*Karamanoğlu Mehmetbey University, Faculty of Medicine, Department of Biostatistics, Karaman, Türkiye*

Abstract

Introduction: Accurate prediction of birth weight is crucial for both fetuses and mothers. Low birth weight (birth weight < 2500g) and high birth weight (birth weight > 4000g) can lead to high perinatal mortality rates, various complications, and both short-term and long-term health outcomes such as chronic diseases. This article aims to propose a machine-learning solution to enhance the accuracy of birth weight prediction and assist clinicians in identifying potential risks before birth.

Materials and Methods: Seven hundred thirty different fetuses between weeks 15-40 were analyzed using clinical data. Nine different regression models from supervised machine learning methods, including logistic regression, support vector machine, decision tree, elastic net regressor, lasso regressor, ridge regressor, artificial neural network, random forest, and k-nearest neighbors algorithms, were employed to predict fetal birth weights based on gestational week, maternal age, gender, and ultrasound measurements, including biparietal diameter, abdominal circumference, and femur length.

Results: Our study revealed that abdominal circumference was the most influential parameter, while gender had the least impact. The performance of the nine different algorithms in birth weight prediction was compared, and the elastic net regressor algorithm exhibited the best predictive performance. The proposed model yielded a prediction result with an average absolute error percentage of 8.87% and an average error of ±284g. A new formula for the newborn weight prediction model was developed using the elastic net regressor machine learning method.

Conclusion: Our study demonstrates that the model created with the elastic net regressor algorithm can predict birth weight at any gestational age between weeks 15-40.

Key words: Pregnancy; birth weight; ultrasonography; artificial intelligence; machine learning.

Introduction

The well-being and survival of a fetus in utero are closely linked to intrauterine weight gain because fetuses outside the normal weight range are at increased risk of long-term perinatal morbidity, mortality, and poor growth and development (1). The significance of accurately predicting birth weight is underscored by low birth weight being a risk factor for many adult diseases, reflecting a baby's health in later life (2). Accurate prediction of birth weight plays a crucial role in determining neonatal care requirements. Infants with low birth weight (<2500g) or high birth weight (>4000g) face higher risks of perinatal and postnatal complications compared to those with normal birth weight (2500-4000g). Infants with low birth weight have significantly higher morbidity and mortality rates compared to those with normal birth weight. Potential risks associated with high birth weight include shoulder dystocia, intrapartum asphyxia, trauma, various maternal complications, and some metabolic complications (3). However, birth weight cannot be directly measured before birth and is often roughly estimated based on clinicians' experiences (4). Researchers have attempted to predict fetal birth weight using single or multiple ultrasound measurement parameters (3). The first successful approach involved the core correlation between fetal abdominal circumference measurement and birth weight (5). Subsequently, researchers developed various formulas based on one, several, or all ultrasound parameters, such as abdominal circumference (AC), biparietal diameter (BPD), femur length (FL), head circumference, and transverse abdominal diameter (6). It has been shown that these formulas, and consequently fetal biometry, are influenced by environmental and socioeconomic factors and ethnic background (7) Artificial neural networks and machine learning are models that mimic the functions of biological.

*Corresponding Author: Ahmet DURSUN, Karamanoğlu Mehmetbey Üniversitesi, Yunus Emre Yerleşkesi, Tıp Fakültesi Dekanlık Binası, Kat 2, Oda 203, 70200, Merkez-Karaman/Türkiye E-mail: dr.ahmetdursun@hotmail.com
Orcid: Özlem Dülger : 0000-0003-0400-1513 , Ahmet Dursun 0000-0003-4568-8761 , Usame Ömer Osmanoğlu 0000-0002-1198-2447

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neurons. The capability of a single neuron can be significantly enhanced by connecting multiple neurons in layers. Artificial neural networks and machine learning methods are widely used powerful, non-linear models for classifying different data types. A neural network consists of several layers of neurons. Neurons in the adjustment layers are connected with relative and quantitative weights. These ratios are selected randomly, modified, and updated through the training procedure to minimize the error rate (8).Recently, machine learning technologies have also been utilized to predict birth weight. Traditionally, estimating birth weight in Turkey relies on regression models based on ultrasound measurements using multiple parameters created by foreign academicians. Due to individual differences in different populations, using these methods to predict fetal birth weight in Turkey may lead to errors, especially for babies with high or low birth weights. In this study, we attempted to calculate the birth weights of infants with known birth weights at various gestational weeks using different machine learning algorithms based on fetal parameters commonly used in pregnant women in the Karaman region, including AC, FL, BPD parameters, and maternal age, gestational week according to the last menstrual period, and fetal gender parameters.

Materials and Methods

The study population consisted of 730 uncomplicated pregnancies of women who applied for routine pregnancy follow-up at Training and Research Hospital between 01/11/2021 and 31/08/2022. The study was conducted retrospectively. Only pregnant women living in the Karaman region, who were citizens of the Republic of Türkiye, and giving birth at the same hospital were included in the study. Gestational age was calculated based on the last menstrual period. Gestational week was calculated in weeks, and patients between 15 and 40 weeks were included in the study. Pregnant women with accompanying diseases that could affect fetal growth (such as diabetes mellitus, hypertension, kidney disease, thyroid disease) and those with known pregnancy complications (such as bleeding and preeclampsia) during ultrasound screening were excluded from the study. Pregnant women with detected fetal malformation during ultrasound examination were also excluded. Patients with a history of obstetric complications were also excluded. Each fetus was measured and included only once. Measurements were made by a Gynecology and Obstetrics specialist with 23 years of experience. For each patient, maternal age, gestational week based on the last menstrual period, and commonly used parameters in ultrasound measurements, including AC (abdominal circumference), FL (femur length), and BPD (biparietal diameter), were measured and recorded. The fetuses gestational weeks and birth weights (in grams) measured during the inclusion in the study were recorded. The fetal gender was determined by ultrasound when it could be identified, and the genders were confirmed after birth.

Ethical approval: The study was approved by the Karamanoglu Mehmetbey University Medical Faculty Clinical Research Ethics Committee on 27.04.2022 with the approval number 15.

Statistical analysis: In our study, the dependent variable is the fetal birth weight. The independent categorical variable is fetal gender. The independent numerical variables include AC, FL, BPD parameters, maternal age, and gestational week according to the last menstrual period. We employed supervised machine learning methods, specifically regression models, for predictions in our study. Logistic regression, support vector machine, decision tree, elastic net regressor, lasso regressor, ridge regressor, artificial neural network, random forest, and k-nearest neighbors algorithms were utilized for nine separate predictions to determine the best-performing prediction model. The success rate in predicting the continuous dependent variable can be assessed through error terms. Performance metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Max Error (ME), were compared and evaluated. The model with the lowest MAE value was considered the best model. All artificial intelligence processes and graphics were conducted using Python version 3.7.9 (Delaware, USA, 2020) software. Python coding involved leveraging libraries such as Keras, pandas, NumPy, matplotlib.pyplot, seaborn, statistics, scipy, statsmodels.formula.api, statsmodels.api, sklearn, and lime. A 5-fold cross-validation was applied to enhance the reliability of model performance, using 80% of the dataset for training and 20% for testing. The impact of statistically significant independent variables on the dependent variable was calculated using the Gradient Boosting Regressor model. The statistical significance level was set at $p < 0.05$.

Table 1: Percentage distribution of the baby's gender, which is a categorical variable.

	N	%
Female	353	48.4
Male	377	51.6
Total	730	100

Results

A total of 730 cases were deemed suitable for the final analysis. The mean ± standard deviation of birth weight was approximately 3237.86±398.58 grams. Generally, 51.6% of newborns were male, and 48.4% were female (Table 1). Maternal age ranged from 18 to 43, averaging 27.68±4.99 years. The gestational weeks of fetuses, measured according to the last menstrual period, ranged from 15 to 40 weeks, with an average of 28.29±7.61 weeks. Other maternal and neonatal details are presented in Table 2. In our study, the birth weights of cases ranged from 2010 to 4610 grams. Twenty-three cases (3.1%) had a low birth weight of less than 2500 grams, while 20 cases (2.7%) had a high birth weight of over 4000 grams.

Table 2: Descriptive statistics of the parameters used (n=730).

Parameter	Average	Standard Deviation	Median	Q1-Q3	Minimum-Maximum
Birth weight (grams)	3237.86	398.58	3270.00	2966.25-3500.00	2010.00-4610.00
AC (mm)	238.48	78.98	253.30	170.60-307.68	83.00-370.70
FL (mm)	51.89	17.79	56.50	37.00-66.83	12.10-79.20
BPD (mm)	70.24	20.17	76.20	52.00-87.80	25.50-102.70
Maternal age (year)	27.68	4.99	27.00	24.00-30.25	18-43
Gestational week	28.29	7.61	29.00	22.00-35.00	15-40

AC: Abdominal circumference; **FL:**Femur length; **BPD:** Biparietal diameter.

The birth weight of 687 cases (94.2%) fell within the normal range of 2500 to 4000 grams (Figure 1).

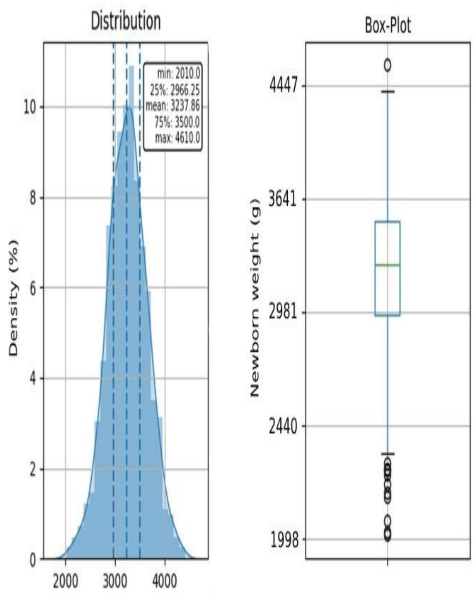

Figure 1: Newborn weight distribution Histogram and Box-Plot Graph.

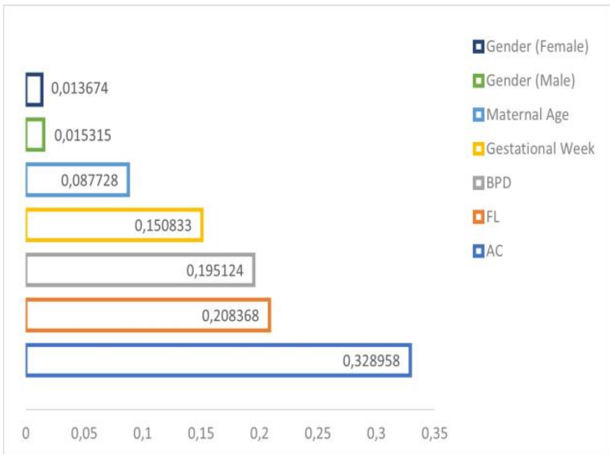

Figure 2: Importance values of variables in the prediction model affecting the dependent variable. AC: Abdominal circumference; FL: Femur length; BPD: Biparietal diameter.

Figure 2 illustrates the graph showing the importance of variables in influencing the dependent variable in the prediction model. Our study revealed that the most influential parameter was AC, while gender had the least impact. Performance results of newborn weight

Table 3: Performance results of machine learning algorithms.

Algorithms	MAPE	MAE	RMSE	ME
ENR	8.870	284*	370	-1004
LR	8.873	285	371	-1007
LAR	8.873	285	371	-1008
RR	8.873	285	371	-1008
ANN	8.873	285	371	-1007
RF	9.537	309	386	-997
SVM	9.289	300	387	-1077
KNN	9.659	314	398	-1256
DT	12.488	401	504	-1420

MAPE: Mean Absolute Percent Error; **MAE:** Mean Absolute Error; **RMSE:** Root Mean Squared Error; **ME:** Maximum Error; **LR:** Linear Regression; **SVM:** Support Vector Machine; **DT:** Decision Tree; **ENR:** Elastic Net Regression; **LAR:** LASSO Regression; **RR:** Ridge Regression; **ANN:** Artificial Neural Network; **RF:** Random Forest; **KNN:** K-Nearest Neighbors; * The lowest MAE value.

Formula 1: Newborn weight (g) prediction model equation based on the elastic net regressor (ENR) machine learning method.

$$\text{Birth Weight} = 3835.41 + 7.16 \times (AC) - 4.59 \times (FL) + 2.47 \times (BPD) - 73.02 \times (\text{Gestational week}) \\ - 3.12 \times (\text{Maternal age}) + 19.77 \times (\text{Genders}\ [\text{male} = 1, \text{female} = 0])$$

AC:Abdominal circumference; **FL:**Femur length; **BPD:** Biparietal diameter.

predictions with artificial intelligence algorithms are presented in Table 3. The performance of nine different algorithms in predicting birth weight was evaluated primarily based on MAE, MAPE, RMSE, and ME parameters. The model with the lowest MAE value was considered the best (Table 3) (9). When predicting newborn weight using AC, FL, BPD, maternal age, gestational week according to the last menstrual period, and gender parameters, the elastic net regressor (ENR) algorithm, with the lowest MAE value (284 grams), demonstrated the best prediction performance. The prediction model generated by the ENR machine learning method is illustrated in Formula 1.

Discussion

Serial ultrasound measurements, especially when used according to established international standards, continue to be the most reliable and accurate method for determining fetal growth (10). Obstetricians can assess abnormal fetal development and reasonable body weight based solely on current results. However, observing the growth trend of the fetus in each pregnancy period may not always be possible, leading to a decrease in diagnostic accuracy. In this study, ultrasound examination data of pregnant women were compiled, and a multidimensional data structure was created by scanning appropriate sample data. The relationship between measurements such as AC, BPD, FL parameters, and birth weight measured by ultrasound was attempted to be revealed. By employing this method, which involves integrating multi-channel data information with the robust capabilities of computers and an efficient machine learning algorithm model, researchers can predict fetal birth weight between 15-40 weeks. This predictive capability could be precious in regions where routine obstetric ultrasound services are not readily accessible (11). A retrospective study conducted in rural Uganda identified low birth weight, considered a marker of prematurity, as a significant risk factor for neonatal mortality, recommending close monitoring before and after birth. Increasing the use of ultrasound scans has been suggested as an effective strategy to reduce this rate (12). We believe that the ability to predict birth weight with ultrasound at any stage of pregnancy will enhance the likelihood of a more meticulous pregnancy monitoring process for parents, particularly for mothers. This enhanced monitoring, in turn, can reduce risks such as low and high birth weight. As a result, it will contribute to increased survival rates for both mothers and babies, reducing hospitalization periods and rates. Farmer et al. considered an approximately 10% error associated with regression analysis methods for ultrasonographic estimation of fetal weight in suspected macrosomic fetuses clinically unacceptable. They conducted ultrasonographic measurements, including biparietal diameter, head and abdominal circumference, femur length, subcutaneous tissue of the abdomen, and amniotic fluid index, for 100 patients suspected of having a macrosomic fetus. By developing an artificial neural network model, they achieved an average error rate of 4.7% compared to actual birth weight, showing that the results of the artificial neural network were superior to traditional regression analysis (13). Feng et al. used the synthetic minority oversampling technique (SMOTE) with the support vector machine (SVM) algorithm for fetal weight classification to improve the accuracy of fetal weight prediction and help clinicians identify potential risks before birth. Finally, a deep belief network (DBN) was used to predict fetal weight based on different ultrasound parameters, and the proposed model achieved a 6.09% error rate (14). Kuhle et al. referred to real clinical values in the birth weight classification (low, normal, and high birth weight) for different pregnancies and compared and analyzed the prediction accuracy of logarithmic weight classification and machine learning methods (15). The cases in our study involved pregnancies with a healthy singleton fetus, documented by ultrasound measurements of AC, FL, and BPD parameters. We chose these three parameters as inputs in our study due to their ease of measurement and frequent use in the literature. Fetuses with significant prenatal diagnoses of structural anomalies, including but not limited to holoprosencephaly, omphalocele, and cystic hygroma, were excluded from the study. In our study, the MAE between estimated fetal weight and actual fetal weight was lowest in the ENR model, with an MAE of 284g and MAPE of 8.87%. The highest error was observed in the decision tree (DT) model, with an MAE of 401g and a MAPE of 12.48%. The relatively superior performance of the ENR model among the other eight methods in our study may be attributed to the high correlation among the independent variables in the model (multicollinearity issue), as ENR is known to yield better results in such cases (16). In a study by Mohammadi et al., who used artificial neural networks, a comparison between ultrasound assessments conducted within the last three days before birth and actual birth weights resulted in a fetal weight prediction with MAE = 162.71g and MAPE = 7.81%. In our study, these figures were 284g and 8.87%, respectively, in the ENR model. [8] Feng et al. found MAE to be 198.55g and the mean absolute percentage error to be 6.09% in their study based on ultrasound measurements taken in the last seven days (14). In a study by Trujilo et al., using Support Vector Machine on 9 to 14-week fetuses with 23 variables related to both mother and baby, they found an MAE of 287.6g (17).

Study limitations: Fetuses with rare structural non-anomalies, which can only be diagnosed postnatally through genetic screening or metabolic methods, and those where no structural abnormality could be demonstrated in prenatal ultrasound examinations, were not excluded. However, due to the rarity of these structural non-anomalies, we believe this point will have minimal impact on the study.

Conclusions

We believe that the differences between our study and others may stem from the broad age distribution of fetuses in our study, ranging from 15 to 40 weeks. Despite this wide range, we find it significant that our results closely match the error rates in birth weight prediction models determined by ultrasound examinations conducted within 3-7 days before birth. In conclusion, our study demonstrates that our ENR model is a reliable predictor for birth weight at any fetal age between 15-40 weeks. However, further research is needed for more accurate birth weight predictions.

Ethical approval: Ethics Committee permission was obtained from Karamanoglu Mehmetbey University Medical Faculty Clinical Research Ethics Committee with the decision number 15 on 04.27.2022.

Conflict of interest: The authors have no conflict of interest regarding this study.

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Author contributions: Concept (ÖD, AD, UÖO), Design (ÖD, AD, UÖO), Data Collection and/or Processing (ÖD), Analysis and/or Interpretation (AD, UÖO), Literature Review (AD), Writing - Original Draft (ÖD, AD), Software and Visualization Support (UÖO)

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