Dola and Valderrama
BMC Medical Informatics and Decision Making (2024) 24:367
https://doi.org/10.1186/s12911-024-02783-x

BMC Medical Informatics and Decision Making

RESEARCH Open Access

Exploring parental factors influencing low birth weight on the 2022 CDC natality dataset

Sumaiya Sultana Dola[1†] and Camilo E. Valderrama[1,2*†]

Abstract

Background and aims Low birth weight (LBW), known as the condition of a newborn weighing less than 2500 g, is a growing concern in the United States (US). Previous studies have identified several contributing factors, but many have analyzed these variables in isolation, limiting their ability to capture the combined influence of multiple factors. Moreover, past research has predominantly focused on maternal health, demographics, and socioeconomic conditions, often neglecting paternal factors such as age, educational level, and ethnicity. Additionally, most studies have utilized localized datasets, which may not reflect the diversity of the US population. To address these gaps, this study leverages machine learning to analyze the 2022 Centers for Disease Control and Prevention's National Natality Dataset, identifying the most significant factors contributing to LBW across the US.

Methods We combined anthropometric, socioeconomic, maternal, and paternal factors to train logistic regression, random forest, XGBoost, conditional inference tree, and attention mechanism models to predict LBW and normal birth weight (NBW) outcomes. These models were interpreted using odds ratio analysis, feature importance, partial dependence plots (PDP), and Shapley Additive Explanations (SHAP) to identify the factors most strongly associated with LBW.

Results Across all five models, the most consistently associated factors with birth weight were maternal height, pre-pregnancy weight, weight gain during pregnancy, and parental ethnicity. Other pregnancy-related factors, such as prenatal visits and avoiding smoking, also significantly influenced birth weight.

Conclusion The relevance of maternal anthropometric factors, pregnancy weight gain, and parental ethnicity can help explain the current differences in LBW and NBW rates among various ethnic groups in the US. Ethnicities with shorter average statures, such as Asians and Hispanics, are more likely to have newborns below the World Health Organization's 2500-gram threshold. Additionally, ethnic groups with historical challenges in accessing nutrition and perinatal care face a higher risk of delivering LBW infants.

Keywords Low birth weight, Machine learning, Interpretable predictive models, Parental factors, Maternal health, Statistical analysis

†Sumaiya Sultana Dola and Camilo E. Valderrama contributed equally to this work.

*Correspondence:
Camilo E. Valderrama
c.valderrama@uwinnipeg.ca
Full list of author information is available at the end of the article

Background

The birth weight of a newborn is a crucial determinant of their survival chances because, according to the World Health Organization (WHO), a newborn weighing less than 2500 grams is at increased risk of dying in the first 28 days of life [1]. Moreover, low birth weight (LBW) is associated with morbidity because those who survive may experience long-term physiological, neuropsychiatric, cognitive, and social challenges that persist into adulthood [2].

LBW is currently a public health issue in the United States (US), which reports more cases than any other Western European country [3]. Recent data show a 1% increase in LBW from 8.52% in 2021 to 8.60% in 2022, with a rise of 20% since 1980 [4]. As of 2022, 8.6% of the US newborns were born with LBW, with Black newborns experiencing the highest LBW rate (14.0%), followed by Asian/Pacific Islanders (9.0%), American Indian/Alaska Natives (8.3%), and Whites (7.2%). Surprisingly, the likelihood of LBW births among Black newborns was double that of White newborns [5]. These ethnic differences were also reported by Paige et al. [6] after analyzing LBW incidents in more than 113,760 singleton live births in King County, Washington, from 2008 to 2012. The results showed that women from certain ethnic groups who were born outside of the US had a lower chance of having an LBW newborn than females who were born in the US, even after adjusting for common pregnancy complications. The lowest rates of LBW were found in White, Chinese, and Korean women. On the other hand, the highest rates of LBW were found in Filipino, Asian Indian, and non-Hispanic Black women (6.8–7.6%).

According to Morisaki et al. [7], the disparities in birth weight between ethnicities are not attributable to traditional factors like maternal age, socioeconomic status, and behavioral characteristics (e.g., smoking) but to maternal anthropometric factors. They reached this conclusion after reviewing singleton US live births between 2009 and 2012, finding that height, BMI, and specific pregnancy-related factors such as gestational weight gain and preterm birth rates were the most significant factors influencing LBW. Given the strong association between maternal body composition, including height, and birth weight [8], previous studies have suggested the need for alternative methods to identify LBW, as the 2500 g cutoff may not be appropriate for newborns of non-European descent [9].

Similar studies in other countries have also reported an association between maternal physical, socioeconomic, and health factors and LBW newborns. Sharma et al. [10], after reviewing 193 neonates in Chandigarh, India reported that a LBW prevalence of 23.8%, with higher rates observed among newborns whose mothers were under 20 (50.0%), poorly educated mothers (32.6%), and mothers with a pre-pregnancy weight less than 45 kg (50.0%).

Other factors contributing to LBW include health concerns, inadequate prenatal care, lower socioeconomic status, and limited education [11]. These factors negatively impact both the physical and mental health of the mother during pregnancy. The sex of the newborn is also an LBW contributor due to the inherent biological differences in growth patterns between male and female fetuses. According to Broere-Brown [12], there are differences in the weight and other biometrics of male and female fetuses, which leads to different body proportions. Male newborns generally weigh more, are longer, and have larger head circumferences than their female counterparts.

These previous studies have identified some relevant factors influencing LBW, such as maternal age, education, socioeconomic status, and ethnicity [4, 5, 10, 11]. Also, one study has mentioned the strong influence of maternal anthropometric factors on birth weight outcomes [7]. However, although these studies have outlined factors shaping birth weight, they have not evaluated the extent to which these factors intersect to create a parental profile associated with a higher risk of having LBW newborns. Furthermore, their focus has primarily been on maternal health, demographics, and socioeconomic factors, often overlooking potential paternal influences such as the father's age, education level, and ethnicity. Additionally, most of the previous research has been restricted to specific local populations in the US, neglecting the diversity across the US population. Therefore, there is a need for a more comprehensive analysis that incorporates various factors, including paternal predictors, to identify the most significant contributors to LBW across all 50 US states.

One way to correlate different factors to identify those more associated with LBW is to leverage machine learning (ML) and deep learning (DL) predictive models. Unlike traditional statistical methods and statistical hypothesis tests, which cannot accommodate interactions among many variables simultaneously, are limited in their ability to handle collinearity, and require a priori hypotheses about how variables relate with one another [13–17], ML and DL models can handle multiple correlated predictors simultaneously, yielding highly interpretable outcomes [18, 19]. In this way, ML and DL models can provide a practical approach to operationalize identifying population subgroups with a high proportion of LBW.

This study presents an approach based on ML and DL models to correlate multiple factors, including anthropometric, socioeconomic, and demographic factors from both mothers and fathers, to predict LBW in a national US newborn dataset provided by the Centers for Disease Control and Prevention (CDC) [20]. To that aim, we use a range of predictive models, including logistic regression, random forest, XGBoost, conditional inference tree and attention mechanism layers, to determine which factors most significantly influence LBW. Furthermore, for explaining our models and to enhance interpretability, we apply Shapley additive explanations (SHAP) and partial dependence plots (PDP) to the outputs of these predictive models, allowing us to identify both direct and inverse relationships between the factors and birth weight.

Methods

Data source

For this study, we used the 2022 National Natality Dataset, a publicly available file, provided by the Centers for Disease Control and Prevention (CDC) [20, 21]. The dataset comprises information for 3,675,606 birth registrations that occurred in the US in 2022. For each newborn, 227 features are provided, including maternal anthropometric (height and weight), parental demographics (parent's race and education), birth weight, etc. The data was collected from the delivery admission form filled out by the mothers, as well as from the medical records collected before and during delivery, such as the first prenatal care visit date, pregnancy risk factors, and delivery mode.

Predictor variables

The 2022 National Natality Dataset provides 227 features describing births that occurred in the US, from both residents and non-residents. To reduce collinearity between the predictors, as well as reduce the computational cost of building the predictor models, we selected 20 variables out of a total of 227. Our selection was based on previous studies suggesting significant factors influencing birth weight [5, 8, 11, 22, 23]. These variables fall into anthropometric, maternal, paternal, socioeconomic, and ethnicity.

Anthropometric variables generally reflect an individual's physical and biological development through body measurements like height, weight, and body mass index (BMI) [24]. These measurements provide information about the mother's nutrition and health, which are important indicators of the newborn's health. The BMI identifies pregnancy complications caused by being underweight or overweight, which may impact the birth weight [25]. Maternal height and pre-pregnancy weight significantly influence fetal growth together. Taller mothers experience accelerated fetal growth in the first and second trimesters, likely due to genetic factors, whereas maternal weight status increasingly influences intrauterine growth in the third trimester [26]. Overall, taller and heavier mothers tend to give birth to larger newborns.

Parental factors, particularly the mother's age, play a critical role in determining birth outcomes. Younger and older mothers often face increased complications, such as preterm birth and LBW, due to their age [27]. Similarly, older fathers' age is associated with greater genetic abnormalities in offspring. In comparison to fathers aged 20 to 34, those older than 34 years have a 90% higher chance of having an LBW newborn, and teenage fathers have a 20% lower chance [28]. On another note, maternal smoking during pregnancy affects fetal development by shortening the gestation period and reducing fetal growth, leading to LBW [29].

Pregnancy history, including previous live births, stillbirths, or neonatal deaths, also provides insight into potential risks. Mothers who have had two or more successful pregnancies tend to have more newborns with normal birth weight, compared to nulliparous women [30–32]. In contrast, a history of previous fetal loss has been linked to a higher occurrence of abnormalities in pregnancies [33]. This kind of occurrence can physically and mentally affect a mother [34, 35]; as a result, the outcomes are adverse.

Parental education levels significantly influence birth outcomes by affecting access to resources and health literacy [11, 22, 23]. Mothers and fathers with more education tend to get better prenatal care and make healthier lifestyle choices, leading to more favorable birth outcomes. Prenatal care and the frequency of prenatal visits are critical [36], as they ensure timely monitoring and intervention, which are essential for identifying and mitigating risks during pregnancy.

Various studies indicate that birth outcomes are not consistent across different ethnicities [5, 37, 38]. Moreover, the origin of the parents can affect the health of the fetus. Lebron et al. [39] investigate the significant influence of a mother's origin on healthcare access, educational opportunities, and economic stability among Hispanic subgroups. These factors are all related to socioeconomic status and have an impact on mothers and newborn health outcomes, such as breastfeeding, birth weight, and newborn mortality. This study also describes how sociopolitical factors, particularly immigrant policies, directly and indirectly affect these health outcomes through stress, limited healthcare access, and other mechanisms.

Outcome variable

We aim to analyze the factors that influence newborns birth weight. As such, we used the birth weight (DBWT) column to determine the outcome variable. As 2500 grams is the WHO's established cut-off for LBW, we divided the birth records into two classes. Newborns with a birth weight lower than 2500 grams were labeled as "Low Birth Weight" (LBW), and those whose birth weight was higher than 2500 grams were labeled as "Normal Birth Weight" (NBW).

Data filtering

In this study, we focused exclusively on newborns with a gestational age of at least 37 weeks (i.e., COMBGEST ≤ 37) due to the strong correlation between preterm births and low birth weight (LBW) [40–43]. Newborns born before 37 weeks typically have a birth weight below 2500 grams, and including them could skew our analysis. We also excluded non-singleton records, as indicated by the column 'DPLURAL', to prevent confounding factors associated with multiple pregnancies. Records from parents identified as mixed race were excluded to avoid ambiguity in the interpretation of results among ethnicities. Furthermore, we only included infants reported to be alive at the time of the report to avoid bias in our predictions due to medical complications. To assess fetal well-being against the predictor variables, we removed any birth records lacking an APGAR score at 5 minutes. Finally, records with unknown values for the selected predictor and outcome variables were also excluded.

Figure 1 shows the data filtering process. Initially, our dataset included 3,675,606 newborn newborns. After filtering out instances based on gestational age, plurality records, mixed races, infant living at the time of the report, and unknown values, the final dataset contained 2,303,722 instances.

Distribution of the predictor variables

Tables 1 and 2 show the distribution of the 20 predictor variables, separated into numerical and categorical variables, respectively. For the numerical variables, the mean and standard deviation are provided, while for the

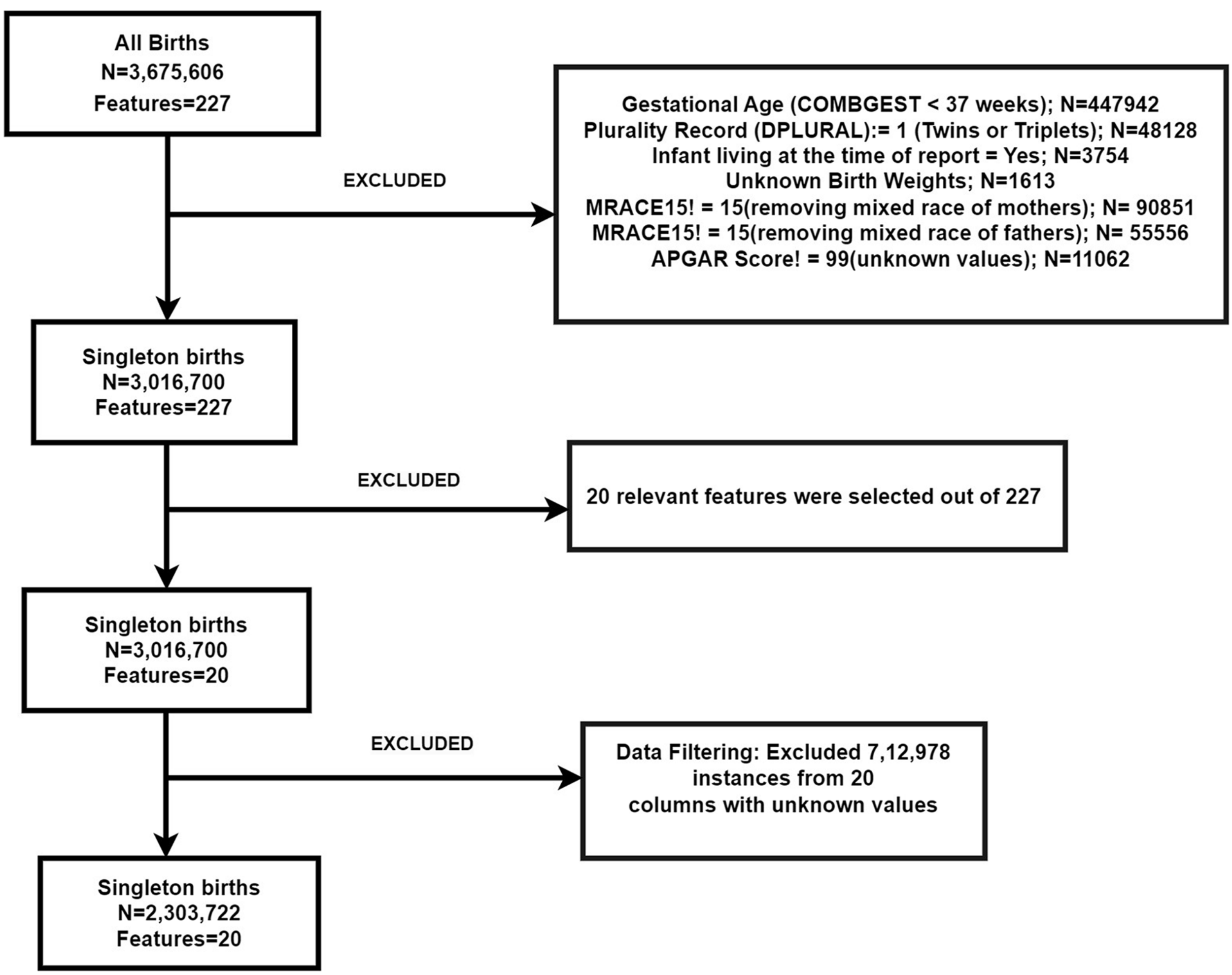

Fig. 1 Data filtering process

Table 1 Description of the 14 numerical predictor variables selected for predicting normal birth weight against low birth weight. For each variable, the mean and standard deviation (SD) is provided

Category	Variable	Description	Mean ± SD
Anthropometric	M_Ht_In	Maternal height (inches)	64.2 (2.8)
	BMI	Body Mass Index	27.5 (6.7)
	PWgt_R	Pre-pregnancy weight (pounds)	161.4 (41.4)
Paternal Factor	FAGECOMB	Parental age (years)	32.0 (6.6)
Maternal Factor	MAGER	Maternal age (years)	29.8 (5.5)
	WTGAIN	Weight gain (pounds)	29.3 (14.7)
	CIG_0	Daily cigarettes before pregnancy	0.5 (3.1)
	CIG_1	Daily cigarettes during 1st trimester	0.3 (2.3)
	CIG_2	Daily cigarettes during 2nd trimester	0.2 (1.9)
	CIG_3	Daily cigarettes during 3rd trimester	0.2 (1.8)
Previous Pregnancies	PRIORLIVE	Prior births now living (count)	1.1 (1.2)
	PRIORDEAD	Prior births now dead (count)	0.0 (0.2)
Prenatal care	PREVIS_REC	Number of prenatal visits (count)	6.9 (1.8)
	PRECARE5	Month prenatal care began	2.8 (1.4)

categorical variables, the number of samples and the relative frequency for each category are displayed. The different subgroups that six parental ethnicities encompassed are displayed in Table 3.

Data preparation

Training and test sets

The final dataset containing 2,303,722 instances was split into training and testing sets. The training set comprised 80% of the data, and the test set comprised 20% of the data. Although our major goal was to combine parental factors to identify those most associated with birth weight outcomes, we used the test set to evaluate the generalization capacity. In detail, given that the test set was not used to fit the predictive models, assessing the models on these independent samples provided a reliable means of evaluating the identified patterns.

To tune the hyperparameters of the machine learning models, we further split the training set into two sets: training and validation. Each hyperparameter configuration was used to train the model, and the validation set was used for performance evaluation. The hyperparameters with the highest performance were selected to train the final model, which was then evaluated in the independent, held-out test data.

To train and evaluate the performance of the predictive models, NBW was labeled '1', while LBW was labeled as '0'. As the dataset was imbalanced, with LBW being the minority class, the models were trained to prioritize the accurate prediction of LBW. This focus was driven by the fact that LBW is a critical health condition that requires proper identification. Consequently, our models were optimized to minimize false negatives (newborns predicted as NBW when they were actually LBW) over false positives (newborns predicted as LBW when they were actually NBW).

Data preprocessing

The predictor variables were separated into numerical and categorical variables. The categorical variables were converted into dummy variables using one hot encoding. The numerical variables were scaled using min-max normalization.

Resampling

Because the number of LBW cases in the training set were only around 3%, the training set was imbalanced. To address this issue, we employed Random Over Sampling (ROS) to ensure a more balanced distribution of classes on the training set.

Predictive models

We used logistic regression, random forest, XGBoost, conditional inference tree, and attention mechanisms to predict the two birth weight classes. These models used different non-linear relationships between the predictor variables to classify between LBW and NBW newborns. Together, these five models offer a robust approach for identifying relevant predictors of birth weight, highlighting those that consistently emerged as significant across all predictive methods.

Logistic regression converted the combination of predictors variables into probabilities using the sigmoid function, thus indicating which combinations had higher odds to belong to the NBW class. To train logistic regression, we used the majority category on the categorical

Table 2 Description of the 6 categorical predictor variables selected for predicting normal birth weight against low birth weight. For each variable, the number of categories

Category	Variable	Description	Number (percent)	
Ethnicity	MRACE15	Maternal ethnicity	White	1,357,994 (59.0)
			Hispanic	491,418 (21.3)
			Black	267,922 (11.6)
			Asian	167,357 (7.3)
			Indigenous	13,677 (0.6)
			Pacific Islanders	5,354 (0.2)
	FRACE15	Paternal ethnicity	White	1,356,042 (58.9)
			Hispanic	457,292 (19.9)
			Black	319,525 (13.9)
			Asian	151,372 (6.6)
			Indigenous	13,534 (0.6)
			Pacific Islanders	5,957 (0.3)
Newborn sex	SEX	Newborn's sex	Male	1,173,414 (50.9)
			Female	1,130,308 (49.1)
Socioeconomic	MEDUC	Maternal education level	8th grade or less	51,656 (2.2)
			9th through 12th grade with no diploma	124,089 (5.3)
			High school graduate or GED completed	530,308 (23.0)
			Some college credit, but not a degree	401,453 (17.4)
			Associate degree (AA, AS)	209,008 (9.1)
			Bachelor's degree (BA, AB, BS)	60,3961 (26.2)
			Master's degree (MA, MS, MEng, MEd, MSW, MBA)	295,846 (12.8)
			Doctorate (PhD, EdD) or Professional Degree (MD, DDS, DVM, LLB, JD)	87,401 (3.8)
	FEDUC	Paternal education level	8th grade or less	62,893 (2.7)
			9th through 12th grade with no diploma	155,774 (6.8)
			High school graduate or GED completed	683,298 (29.7)
			Some college credit, but not a degree	404,908 (17.6)
			Associate degree (AA, AS)	174,720 (7.6)
			Bachelor's degree (BA, AB, BS)	527,983 (22.9)
			Master's degree (MA, MS, MEng, MEd, MSW, MBA)	204,495 (8.9)
			Doctorate (PhD, EdD) or Professional Degree (MD, DDS, DVM, LLB, JD)	89,651 (3.89)
	MBSTATE_REC	Maternal origin	US born	1,819,958 (79.0)
			born outside	483,764 (21.0)

Table 3 Detailed breakdown of ethnic categories of parents

Ethnicity of parents	Categories
White	
Black	
Asian	Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, Other Asian
Hispanic	Mexican, Puerto Rican, Cuban, Central or South American, Dominican, Other and unknown Hispanic
Indigeneous	American Indian and Alaska Native
Pacific Islander	Native Hawaiian and Other Pacific Islander

variables as a reference (see Table 2). Thus, for both maternal and paternal ethnicity, the reference category was White; for newborn sex, the reference was male; for maternal education level, the reference was a Bachelor's degree; for paternal education, the reference was a high school graduate; and for maternal origin, the reference was US-born.

Random forest (RF) and XGBoost built multiple decision trees to identify rules more associated with LBW and NBW. Each tree was built by using a subset of training data and a subset of the predictors variables that were selected randomly. The difference between RF and XGBoost is the way the individual trees were combined. RF used a bagging strategy, in which the trees are trained independently. In contrast, XGBoost used a boosting strategy, in which trees were trained sequentially aiming that each new tree corrected the mistakes made by the previous ones.

The conditional inference tree (CIT) built a tree relating the predictors based on their capacity to separate samples in two groups that were statistically significantly different [44]. To that aim, the CIT evaluated multiple hypothesis tests with Bonferroni correction to find the predictor variable that produces the lowest pvalue to discriminate between LBW and NBW cases.

The attention layer mechanism is a deep learning model that identifies the variables that a model focuses on the most when making predictions [45]. This was achieved using three matrices, query (Q), key (K), and value (V), which were correlated to assign an attention weight to each input feature as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where d_k was the dimension of the keys, and the softmax function ensured that the attention weights sum to 1, normalizing the attention weights. The attention weight highlighted the importance of different input features relative to discriminating between LBW and NBW cases.

Evaluation performance

To evaluate the performance of the models, six different metrics were computed. The first two corresponded to the individual recall for each class. The remaining four corresponded to the average (macro) of the individual class metric for recall, precision, F1-score, receiver operating characteristic area under the curve (ROC AUC), and the precision-recall area under the curve (ROC PR).

Data analysis and interpretation

After training the predictive models, we applied various post-processing methodologies to identify the variables that consistently emerged as significant across all predictive methods. Table 4 shows the different methodologies used to interpret the models. These interpretation methods allowed us to identify the common factors that consistently emerged as relevant across all analyses in distinguishing between NBW and LBW cases.

Table 4 Interpretability methodologies to post-process trained predictive models

Technique	Models
Odd Ratio Analysis	LR
Feature Importance	RF, XGBoost
Attention Weights	Attention Layer
Partial Dependence Plot (PDP)	LR
Conditional Inference Tree	CIT
SHAP Values	LR, RF, XGBoost

Odds-ratio analysis

For logistic regression, we performed odds-ratio analysis to determine which variables significantly correlated with birth weight outcomes, thus identifying those that were strongly associated with LBW.

Feature importance

For the ensemble models, we conducted a feature importance analysis to identify the most influential factors contributing to the predictions. The ensemble models computed importance scores by weighting, summing, and averaging attribute data across all decision trees, identifying the factors that were most sensitive and critical for prediction performance.

Attention weights

Similarly, for the attention mechanism, we visualized the attention scores assigned to each predictor after training the model. Higher attention scores indicated that a particular feature was more relevant for the prediction task.

Conditional inference tree

We visualized the branches of the CIT, with each branch representing a classification rule that offers insights into how different predictor variables are combined to classify NBW and LBW cases. By analyzing these branches, we identified parental profiles associated with the lowest and highest proportions of LBW newborns.

Partial dependence plots

To visualize the marginal impact of a single feature on LBW and NBW cases, we implemented Partial Dependence Plots (PDP) [46] using the logistic regression model. PDPs illustrate how a feature influences the predicted outcome by displaying the average prediction while holding other features constant. Unlike feature importance techniques, PDPs can reveal both the direction and nature of the relationship between a feature and the prediction outcome.

Shapley additive exPlanations

We employed Shapley Additive Explanations (SHAP) to analyze the predictive rules of logistic regression, RF, and XGBoost further. SHAP analysis quantified the contribution of each feature to individual predictions, offering a detailed understanding of the models' behavior. Specifically, the SHAP analysis generated visualizations that illustrate the contribution of each feature to the predictions. The summary plots displayed each variable vertically, with the x-axis representing the range of SHAP values. Positive values on the x-axis indicated a higher likelihood of the predicted outcome, while negative values suggested a lower likelihood. For a specific feature, red points on the right indicated a positive contribution to the likelihood of achieving NBW, whereas blue points on the left indicated a negative impact, reducing the likelihood of NBW. When a feature exhibited a significant contrast between red and blue across both positive and negative SHAP values, it suggested that the feature's effect on the prediction varied considerably across its range.

Result

Model evaluation on the testing set

Table 5 shows the performance on the held-out, independent test samples. All the models achieved an accuracy greater than 64%, with XGBoost showing the highest performance. Overall, the predictive models performed better for predicting NBW than LBW. The macro precision, F1-score, and PR AUC were the lowest metrics due to the high imbalance between NBW and LBW classes, as well as the fact that the models were trained to prioritize the prediction of LBW cases. Consequently, the models obtained a false positive rate for the LBW class around 34%, which, given the high ratio between LBW and NBW samples (1:30), resulted in a low precision for the LBW class. Nevertheless, the average ROC AUC across the models was nearly 70%, indicating that the models were able to effectively distinguish between LBW and NBW cases [47].

Odds ratio analysis

Table 6 shows significant factors ($p\ value < 0.05$) obtained by the logistic regression for predicting NBW (class labeled as '1') and LBW (class labeled as '0'). Maternal anthropometrics showed a strong association with the odds of having NBW newborns. Specifically, taller mothers and those with higher pre-pregnancy weight had higher odds of delivering NBW newborns. In addition to anthropometric factors, the chronological age of both the mother and father showed a negative association with NBW, as the odds of delivering an NBW newborn decreased with increasing parental age.

The logistic regression analysis showed that parental ethnicity correlated with birth weight outcomes. Parents who identified as Black or Asian had higher odds of having LBW offspring than their White counterparts. In contrast, Hispanic mothers were more likely to have newborns with NBW compared to White mothers. Interestingly, mothers who were born outside the US were more associated with NBW newborns than US-born mothers.

Actions taken during pregnancy and previous pregnancy history significantly influenced the odds of delivering NBW infants. For instance, gaining adequate weight during pregnancy and attending prenatal visits were positively associated with having NBW newborns. Conversely, smoking habits during pregnancy negatively impacted the odds of NBW, particularly in the first trimester, where an increase of one unit in daily cigarette consumption decreased the odds of delivering an NBW newborn by 76%. Additionally, the number of previous living births emerged as a critical indicator of NBW outcomes, suggesting that mothers with a history of

Table 5 Performance of the predictive models for classifying low-birth weight (LBW) and normal-birth weight (NBW). Individual recall for each class is presented, along with macro accuracy, recall, macro precision, macro F1-score, macro area under the receiver operating characteristic curve (ROC AUC), and macro area under the precision-recall curve (PR AUC)

Model	LBW recall (%)	NBW recall (%)	Accuracy (%)	Macro recall (%)	Macro precision (%)	Macro F1-score (%)	Macro ROC AUC (%)	Macro PR AUC (%)
LR	64.0	66.0	66.0	65.0	52.0	44.0	70.4	52.9
RF	62.0	66.0	66.0	64.0	52.0	44.0	69.5	52.7
XGBoost	66.0	68.0	68.3	67.0	52.0	46.0	73.4	53.9
CIT	61.6	61.8	61.8	61.7	51.4	43.4	63.8	51.3
Attention Mechanism	64.0	66.0	66.3	65.0	52.0	45.0	70.5	52.9
Average	**63.5**	**65.6**	**65.7**	**64.3**	**51.9**	**44.5**	**69.52**	**52.7**

Table 6 Odds ratios analysis for the logistic regression coefficients. All coefficients were significant at the significance level of 0.05. The top 10 significant features are the mothers who were born outside of us, Asian fathers, fathers with a bachelor's degree, female newborns, Black mothers, month prenatal care began, number of prenatal care visits, number of previous living births, and weight gain

Category	Variable	Coefficient	95% CI	Odds ratio	*P* val
Anthropometric	Maternal height	3.70	(3.45, 4.00)	41.40	< 0.001
	Pre-preganncy weight	1.54	(1.16, 1.92)	4.66	< 0.001
Ethnicity (White as reference)	Mother - Black	−0.53	(−0.55, −0.51)	0.59	0.0
	Father - Asian	−0.53	(−0.55, −0.51)	0.59	< 0.001
	Father - Black	−0.29	(−0.31, −0.27)	0.75	< 0.001
	Mother - Hispanic	0.13	(0.11, 0.15)	1.14	< 0.001
	Mother - Asian	−0.14	(−0.16, −0.11)	0.87	< 0.001
	Mother - Indigenous	−0.28	(−0.39, −0.17)	0.75	< 0.001
	Father - Pacific Islander	−0.11	(−0.17, −0.05)	0.90	< 0.001
Maternal Education (Bachelors degree as reference)	Mother - 9th through 12th grade with no diploma	−0.40	(−0.42, −0.38)	0.66	< 0.001
	Mother - High school graduate or GED completed	−0.20	(−0.21, −0.18)	0.81	< 0.001
	Mother - Some college credit, but not a degree	−0.15	(−0.16, −0.13)	0.86	< 0.001
	Mother - Associate degree	−0.10	(−0.13, −0.09)	0.90	< 0.001
	Mother - 8th grade or less	−0.17	(−0.20, −0.13)	0.84	< 0.001
	Mother - Master's degree	0.05	(0.04, 0.07)	1.06	< 0.001
Paternal Education (High school graduate or GED completed as reference)	Father - Bachelor's degree	0.34	(0.33, 0.36)	1.41	0.0
	Father - Master's degree	0.29	(0.27, 0.31)	1.33	< 0.001
	Father - Some college credit, but not a degree	0.17	(0.16, 0.18)	1.18	< 0.001
	Father - Doctorate or Professional Degree	0.33	(0.30, 0.35)	1.39	< 0.001
	Father - Associate degree	0.18	(0.16, 0.20)	1.20	< 0.001
	Father - 9th through 12th grade with no diploma	−0.06	(−0.08, −0.04)	0.93	< 0.001
	Father - 8th grade or less	0.11	(0.08, 0.14)	1.12	< 0.001
Paternal age	Paternal age	−0.26	(−0.34, −0.17)	0.77	< 0.001
Maternal factors	Weight gain	2.63	(2.60, 2.67)	13.93	0.0
	Maternal age	−0.38	(−0.43, −0.34)	0.68	< 0.001
	Daily cigarettes before pregnancy	−1.64	(−1.82, −1.45)	0.19	< 0.001
	Daily cigarettes in the 1st trimester	−1.39	(−1.78, −0.99)	0.24	< 0.001
	Daily cigarettes in the 3rd trimester	−1.20	(−1.74, −0.66)	0.30	< 0.001
	Daily cigarettes in the 2nd trimester	−1.23	(−1.86, −0.61)	0.29	< 0.001
Newborn sex (male as reference)	Female (1: 'yes', 0: 'no')	−0.21	(−0.21, −0.19)	0.81	0.0
Previous pregnancies	previous living births	3.62	(3.54, 3.69)	37.29	0.0
Prenatal care	Number of prenatal visits	1.03	(1.01, 1.06)	2.81	0.0
	Month prenatal care started	0.60	(0.57, 0.63)	1.82	0.0
Mother origin (Born in the US as reference)	Born Outside the US (1: 'yes', 0: 'no')	0.39	(0.39, 0.40)	1.48	0.0

successful pregnancies have a higher likelihood of delivering NBW newborns.

The educational levels of both mothers and fathers significantly influenced the likelihood of a newborn having a NBW. Mothers with an education level of an associate degree or lower exhibited lower odds of delivering NBW newborns compared to those with a bachelor's degree. Similarly, fathers who completed at least a bachelor's degree had approximately 30% higher odds of having an NBW newborn than those who graduated from high school.

Ensemble models relevant features

Figures 2 and 3 illustrate the feature importance for the random forest and XGBoost models, respectively. For both ensemble models, weight gain during pregnancy emerged as the most important predictor of NBW and LBW cases. Additionally, pre-pregnancy

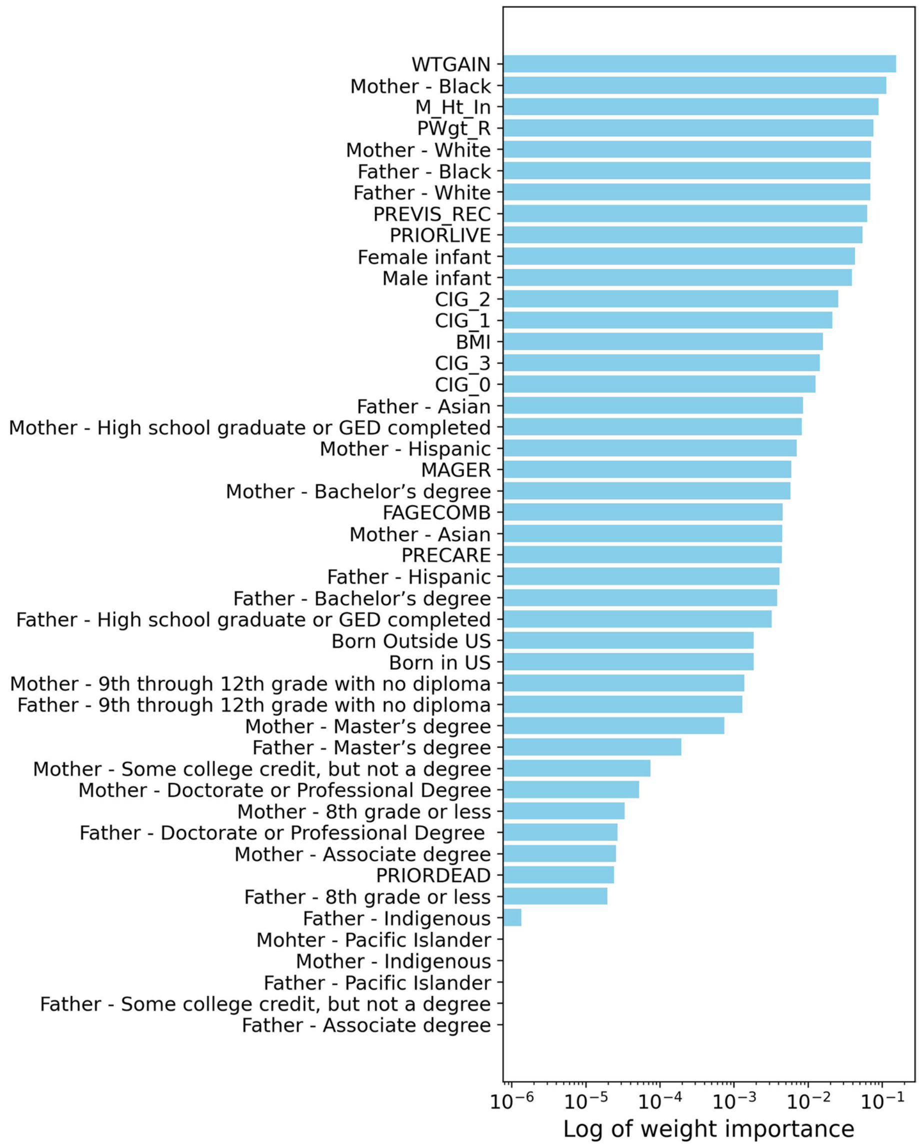

Fig. 2 Feature importance for the random forest (RF) model. The top ten predictors identified as most relevant for birth weight predictions were weight gain (WTGAIN), Black parents, maternal height maternal height (M_Ht_in), pre-pregnancy weight (PWgt_R), number of previous living births (PRIORLIVE), White parents, number of prenatal care visits (PREVIS_REC), and female infants

weight, maternal height, number of prenatal care visits, and previous living births ranked among the top ten features in both models. The random forest and XGBoost also highlighted the significance of paternal factors in predicting birthweight outcomes, revealing that the father's ethnicity (White or Black) and age were critical for classifying LBW and NBW. Notably, neither model included educational factors in their top ten rankings based on feature importance.

Attention mechanism layer

Figure 4 shows the attention scores assigned by the self-attention mechanism to each variable. The bar chart ranks features according to their importance scores, with taller bars indicating greater significance for predicting birth weight. Among the features, the education level of parents exhibited the highest importance. Additionally, the number of prenatal care visits, the presence of Asian fathers, Black mothers, mothers born in the US., the

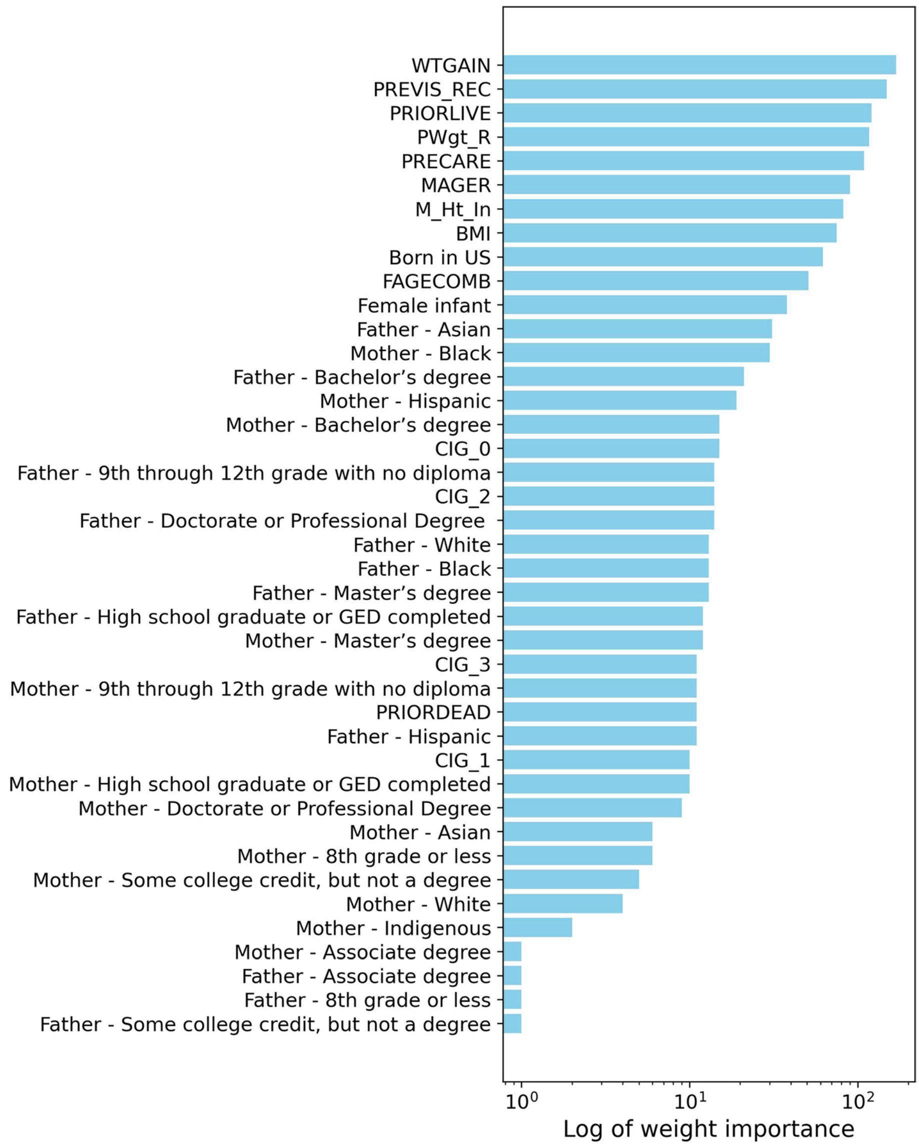

Fig. 3 Feature importance for the XGBoost model. The top ten predictors identified as most relevant for birth weight predictions were weight gain (WTGAIN), number of prenatal care visits (PREVIS_REC), number of previous living births (PRIORLIVE), pre-pregnancy weight (PWgt_R), BMI, month prenatal care began (PRECARE), parental age (MAGER and FAGECOMB), maternal height (M_Ht_in), BMI, mothers who were born in the US

month prenatal care commenced, pre-pregnancy weight gain, maternal height, and weight gain during pregnancy were also among the features that received the highest attention weights.

Partial dependence plots

Figures 5, 6, 7, 8, 9, 10, 11, 12 and 13 show the PDP for nine parental factors based on the logistic regression output, namely: weight gain during pregnancy, maternal height, maternal pre-pregnancy weight, as well as parental ethnicity and education. In the plots, the x-axis represents the range of values for each feature, with numerical features grouped into bins and categorical features represented by individual categories. The distribution of feature values was also displayed along the x-axis. The y-axis shows the predicted change in the model output, with the leftmost value on the x-axis serving as the reference point. To aid interpretation, the PDP of the reference value was set to zero, highlighting relative changes across the feature values.

Figures 5, 6, 7 display maternal anthropometric factors effect on the chances of delivering an NBW newborn. Figure 5 shows a significant upward trend with weight gain during pregnancy, indicating that higher weight gains

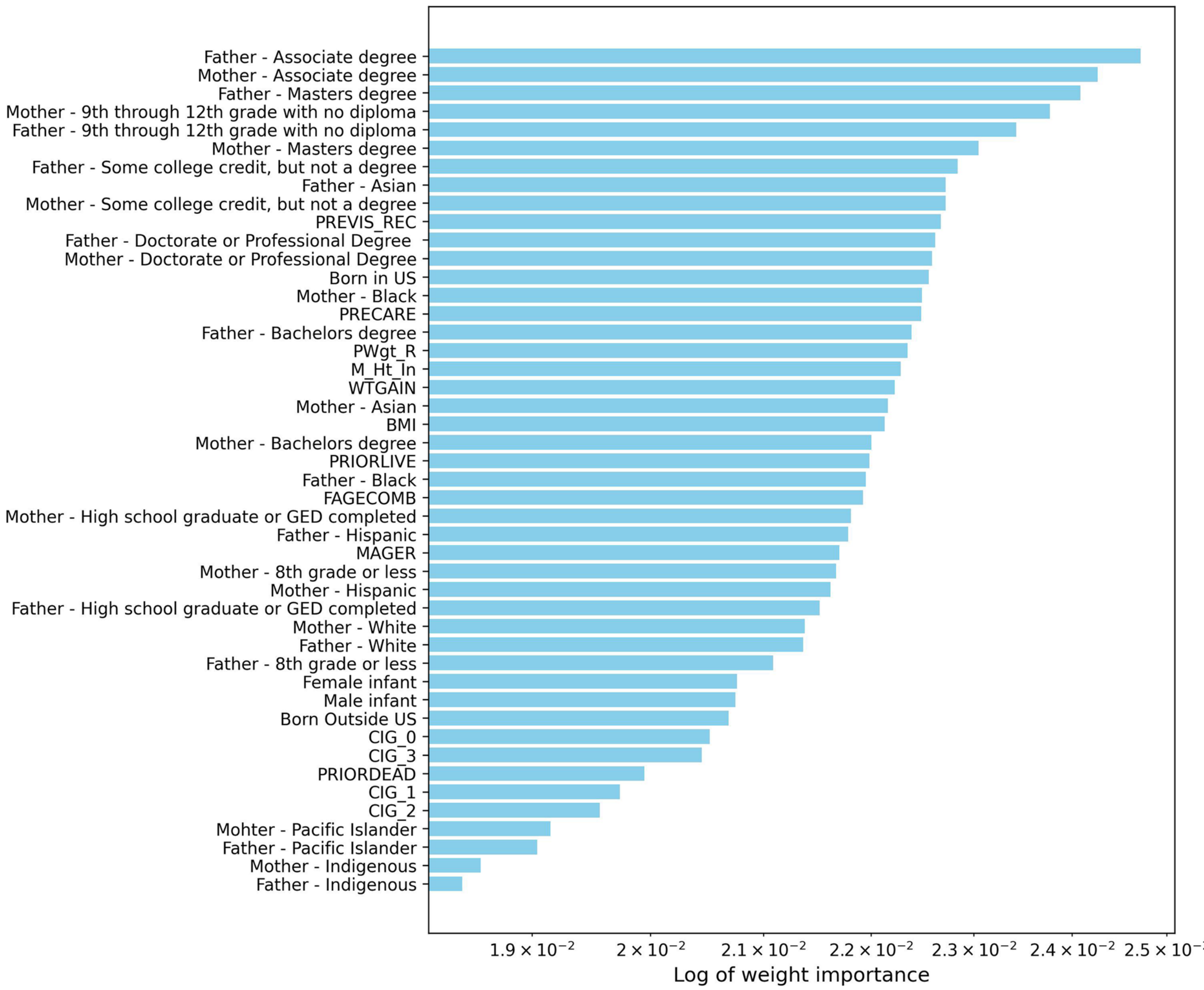

Fig. 4 Feature importance from the attention mechanism layer, based on attention scores assigned to each predictor variable. As a reference, equal relevance for all predictors would result in a score of $1/46 = 2.2\text{x}10^{-2}$. Variables with scores higher than $2.2\text{x}10^{-2}$ contributed the most to the birth weight predictions

were strongly related to NBW outcomes. For maternal height, Fig. 6 indicates that mothers between 61 and 64 inches (155–163 cm) had similar probabilities of delivering an NBW newborn, but these probabilities increased steadily for mothers taller than 64 inches, suggesting that taller mothers were more likely to deliver NBW newborns. In terms of pre-pregnancy weight (Fig. 7), there was an increasing trend, indicating that heavier mothers had more chances to deliver NBW newborns.

Figures 8 and 9 show the effect of parental age on the birth weight prediction. The trend for both parents was inverse, indicating that the older parents were, the lower the probability of having an NBW newborn was.

Figures 10 and 11 show the impact of parental ethnicity on NBW outcomes. In general, White parents had a higher probability of having an NBW newborn than fathers from other ethnicities. Asian and Black parents were those with the highest risk of having an LBW newborn. Among ethnicities, Hispanic mothers were the only group with a higher likelihood of delivering an NBW newborn compared to White mothers.

Figures 12 and 13 show the influence of parental education on birth weight outcomes. Mothers with at least a bachelor's degree were more likely to deliver a newborn with normal birth weight (NBW) compared to those with only a high school diploma or some college credits. Regarding fathers, those who had completed at least an associate degree showed a significantly higher probability of having an NBW newborn.

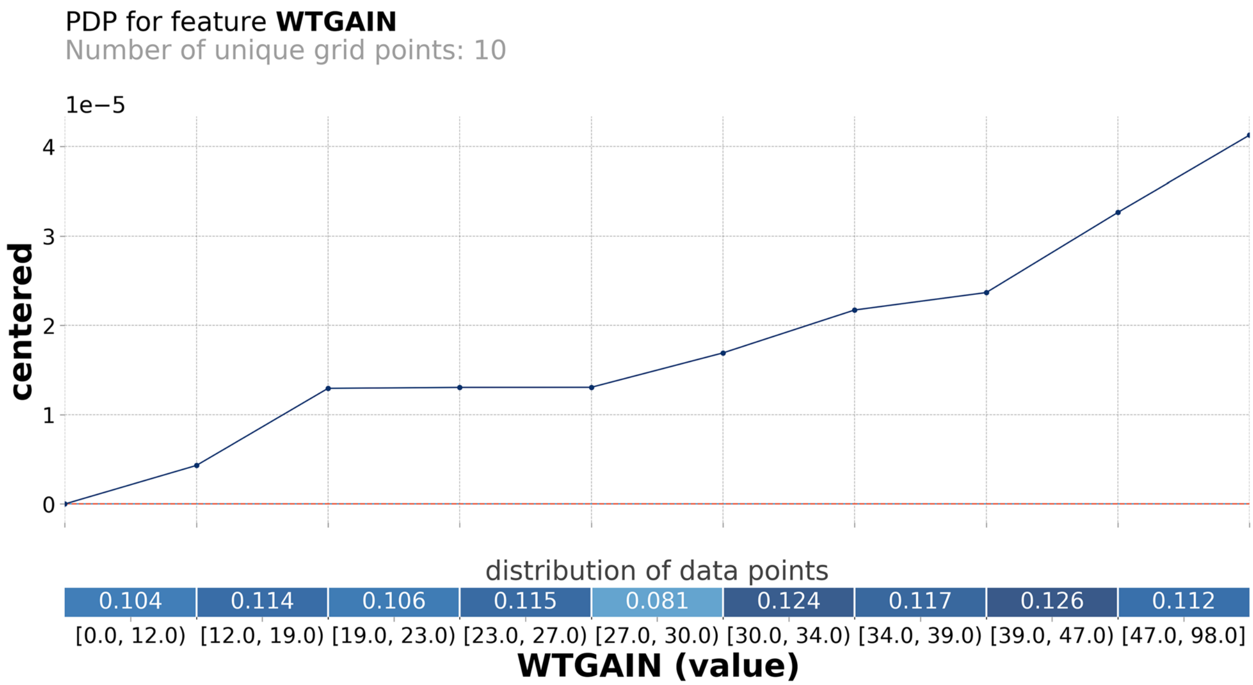

Fig. 5 PDP for maternal weight gain during pregnancy

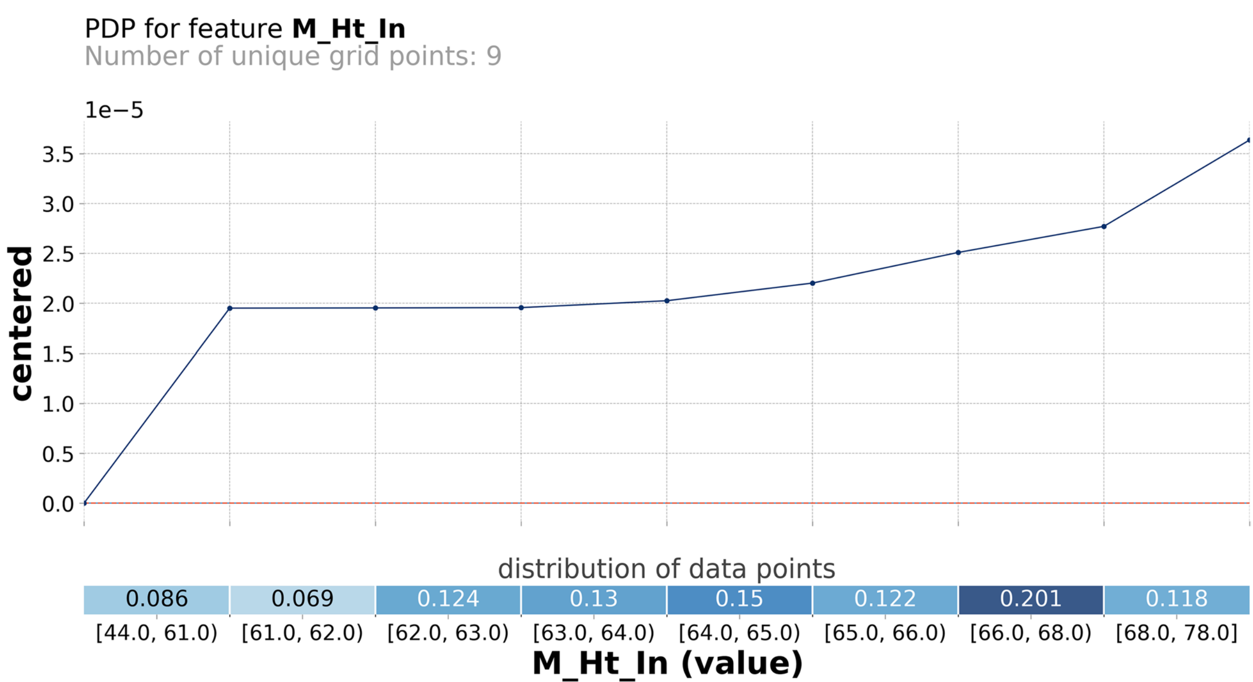

Fig. 6 PDP for maternal height

Conditional inference tree

Figure 14 displays the conditional inference tree when its maximum height was constrained to three levels. Among the different predictor variables, the tree identified that the most critical variables to discriminate between NBW and LBW cases were maternal ethnicity, maternal height, and maternal weight gain.

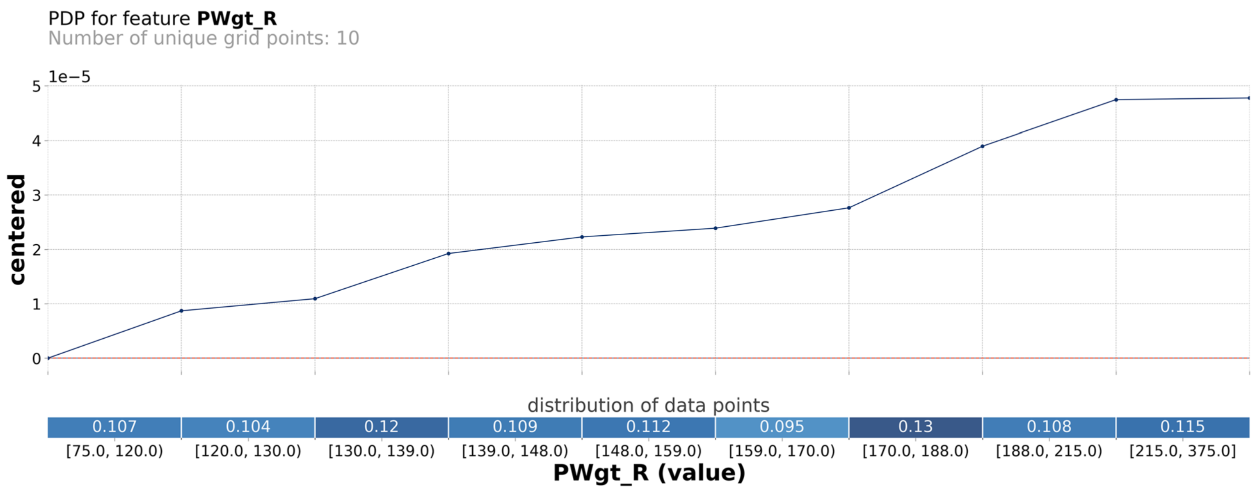

Fig. 7 PDP for pre pregnancy weight

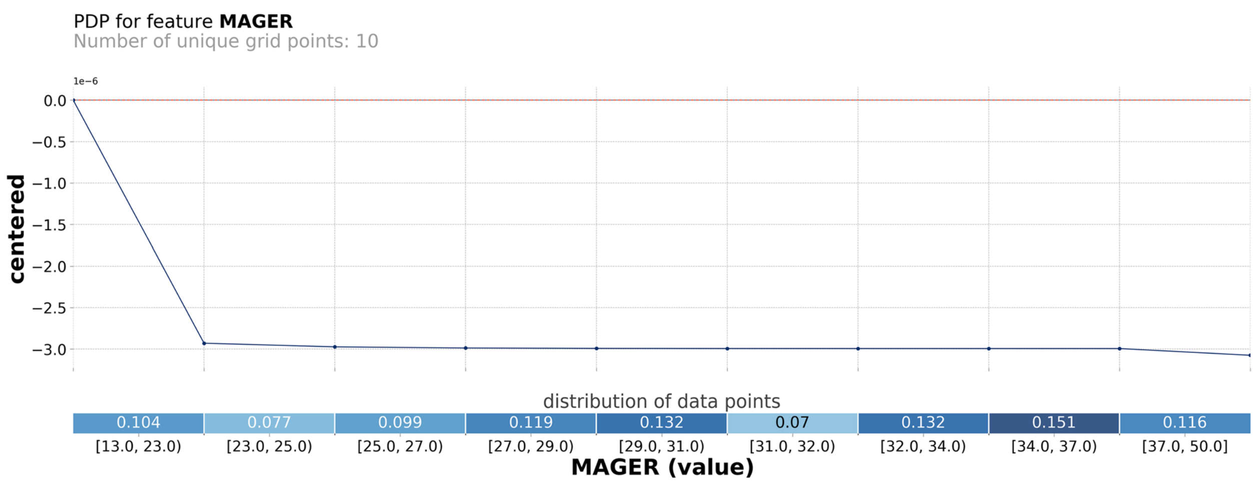

Fig. 8 PDP for maternal age

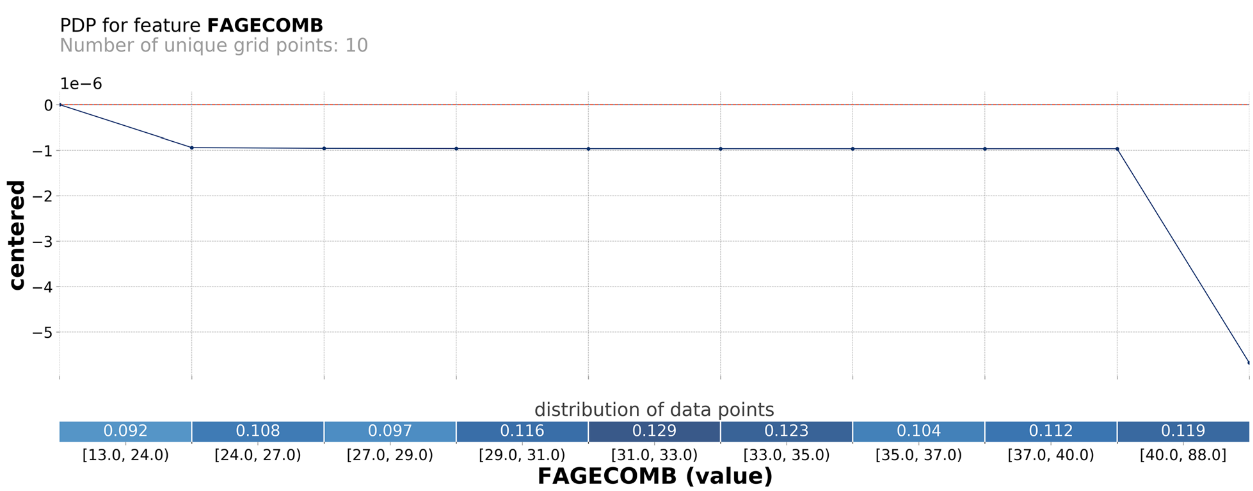

Fig. 9 PDP for paternal age

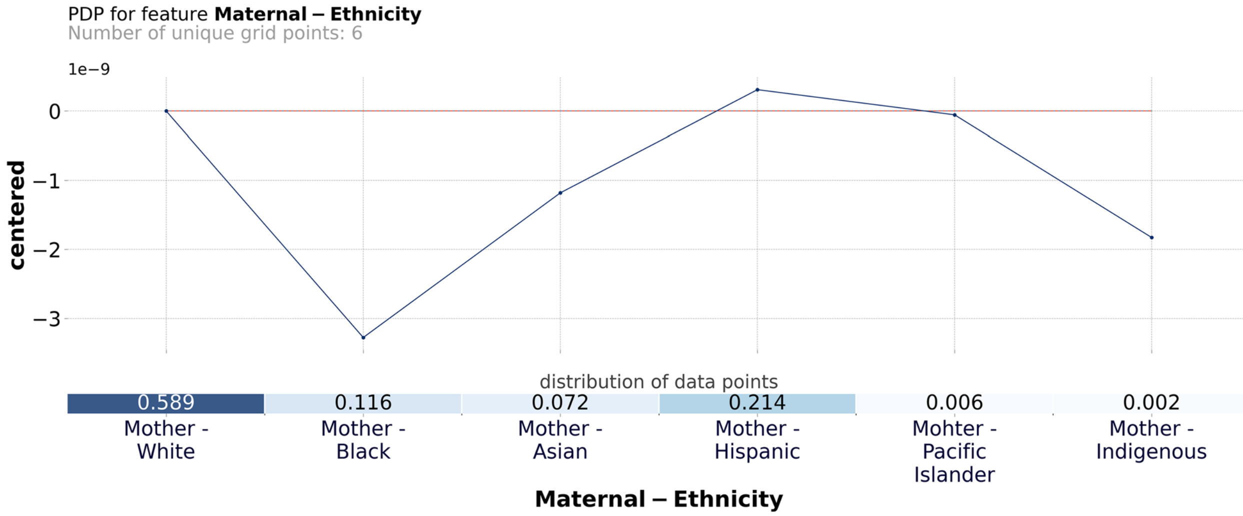

Fig. 10 PDP for maternal ethnicity (Mother - white as reference)

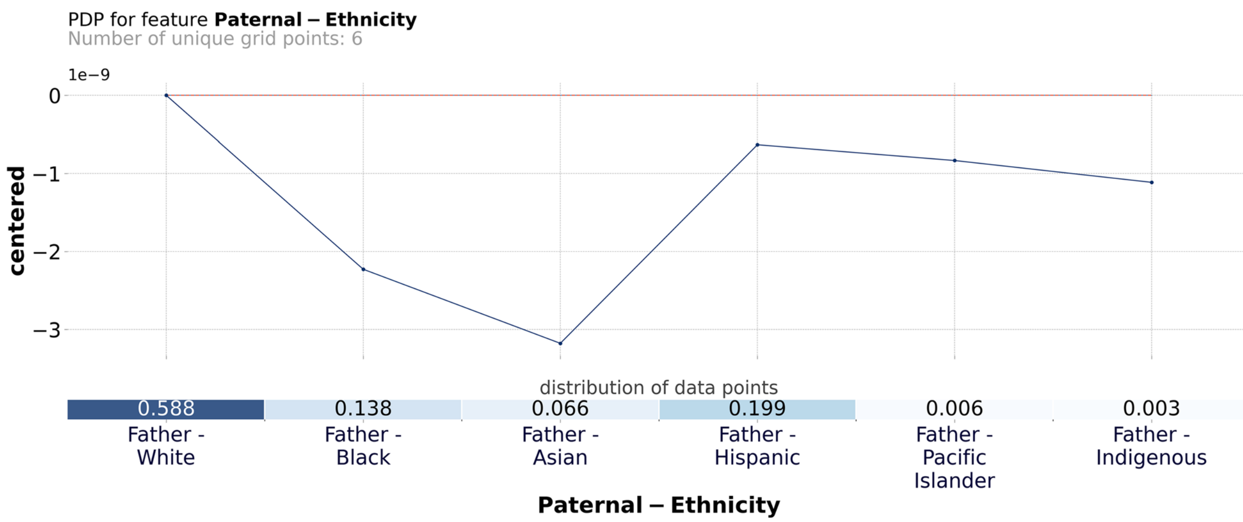

Fig. 11 PDP for paternal ethnicity (Father - white as reference)

Based on maternal ethnicity, the tree was split into two groups: one group included White, Hispanic, Pacific Islander, and Indigenous mothers, whereas the other one encompassed Black and Asian mothers. For the White, Hispanic, Pacific Islander, and Indigenous mothers, the node with the highest proportion of LBW cases corresponded to mothers smaller than 63 inches who gained less than 28 lbs during pregnancy, and whose pre-pregnancy weight was lower than 131 lbs (Node 5; 68.8%). For Black and Asian mothers, the node with the highest proportion of LBW cases was for mothers who gained less than 28 lbs (Node 9; 69.0%).

The node with the highest proportion of NBW newborns (Node 18; 73.6%) corresponded to White, Hispanic, Pacific Islander, and Indigenous mothers taller than 63 inches who gained more than 27 lbs and held a bachelor's, Master's, PhD, or professional degree.

SHAP analysis

Figures 15, 16, and 17 show the top 20 factors based on SHAP values for the logistic regression, random forest, and XGBoost models, respectively. The SHAP summary plots revealed consistent patterns across all models for predicting birth weight. Notably, weight gain during

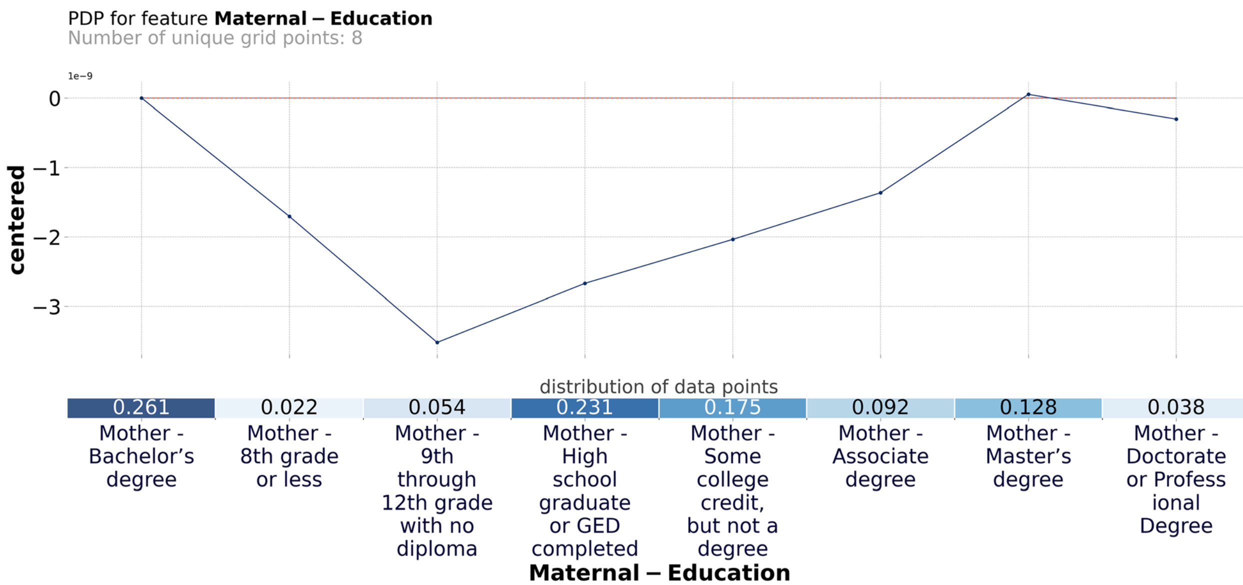

Fig. 12 PDP for maternal education (Mother - bachelor's degree as reference)

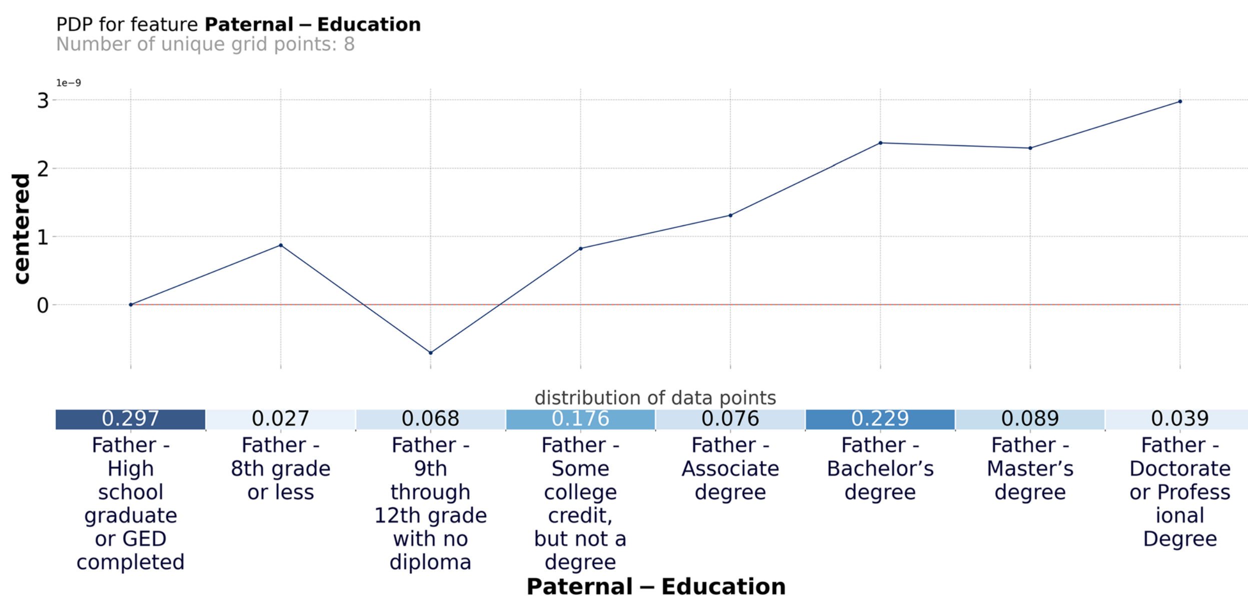

Fig. 13 PDP for paternal education (Father - high school graduate or GED completed as reference)

pregnancy emerged as the most influential predictor, with higher weight gain being strongly associated with delivering an NBW. Additionally, all SHAP analyses highlighted the positive relationship between maternal height (M_Ht_In), body mass index (BMI), pre-pregnancy weight (PWgt_R), and the likelihood of having an NBW newborn.

Parental factors, including ethnicity, age, and education, played a pivotal role in birth weight predictions. In terms of ethnicity, Black, Hispanic, and Asian fathers were more frequently related to LBW predictions, whereas White parents and Hispanic mothers tended to correlate more with NBW predictions. Regarding age, the SHAP analyses indicated that the older the parents were, the higher the chances of having an LBW newborn. Finally, mothers and fathers who had higher education levels, such as master's and bachelor's degrees,

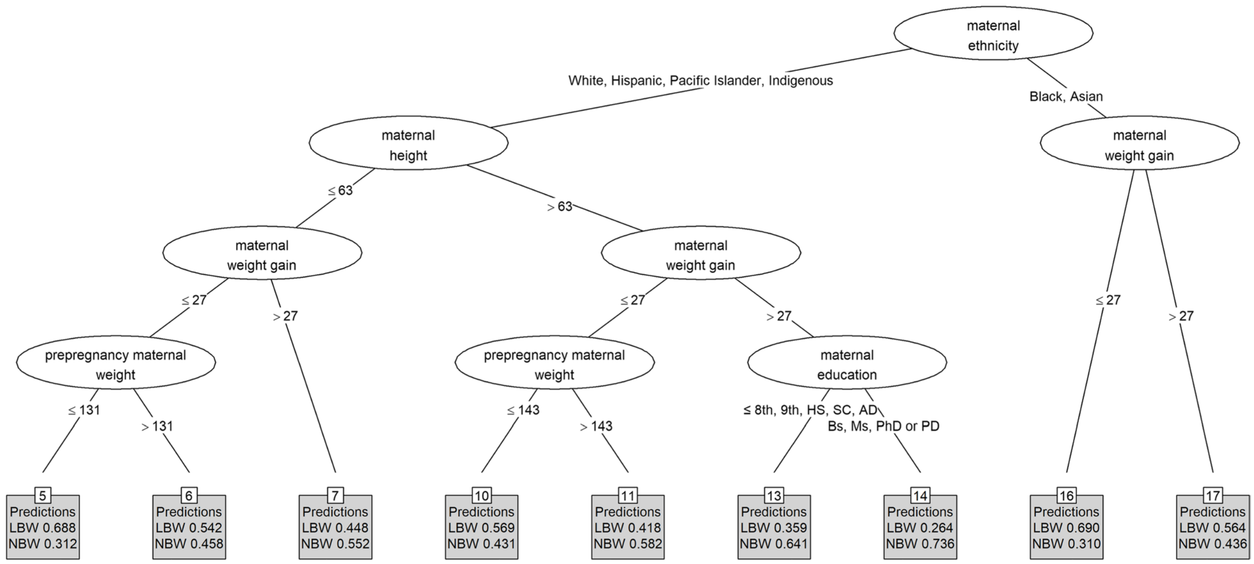

Fig. 14 Conditional Inference Tree for detecting NBW and LBW newborns. For maternal education, the following abbreviation was used: '≤ 8th', for 8th grade or less; '9th', for 9th through 12th grade with no diploma; 'HS', for High school graduate or GED completed; 'SC', for some college credit, but not a degree; 'AD', for Associate degree (AA, AS); 'Bs', for Bachelor's degree (BA, AB, BS); 'MS', for Master's degree (MA, MS, MEng, MEd, MSW, MBA); 'PhD or PD', for Doctorate (PhD, EdD) or Professional Degree (MD, DDS, DVM, LLB, JD)

were found to have a higher likelihood of giving birth to NBW infants.

Previous pregnancy history, particularly the number of living births (PRIORLIVE), was strongly associated with NBW predictions. Likewise, regular prenatal checkups (PREVIS_REC) were positively linked to NBW outcomes. Conversely, negative factors such as maternal smoking during pregnancy (CIG_0, CIG_1, CIG_2, and CIG_3) were associated with LBW predictions. Additionally, the sex of the newborn emerged as a significant factor, with male newborns (SEX_M) more likely to be predicted as NBW, while female newborns (SEX_F) were associated with higher rates of LBW.

Effect of maternal height, ethnicity and birth weight

To further explore the strong association between birth weight outcomes, maternal height, and ethnicity indicated by the predictive models, we conducted a descriptive analysis comparing birth weights ranging from 2200 to 2550 g against newborn well-being, based on the APGAR 5 score, and average maternal height (Fig. 18).

For birth weights near the WHO's LBW cutoff of 2500 g, White and Black newborns exhibited higher rates of abnormal APGAR 5 scores (APGAR 5 < 6) compared to their Asian and Hispanic counterparts. Notably, within this birth weight range, White and Black mothers were, on average, taller than Asian and Hispanic mothers. This pattern suggests that the WHO's LBW cutoff of 2500 g may represent a greater risk for offspring of ethnic groups with taller average maternal heights, such as White and Black mothers, compared to infants born to shorter mothers, such as Asian or Hispanic mothers.

Discussion

Our findings indicate that there are critical parental factors that strongly influence birth weight outcomes on the US population. Across all the analyses, nutritional and maternal anthropometric factors, such as maternal height, weight gain during pregnancy, pre-pregnancy weight, and parental ethnicity, consistently emerged as critical determinants of newborn weight. These findings align with previous research, which also reports that nutritional status and maternal anthropometrics are significantly correlated with birth weight and length of the newborn [7, 48, 49].

The relationship between maternal height, weight gain during pregnancy, pre-pregnancy weight, and maternal ethnicity helps explain why some women are more likely to deliver LBW newborns. For example, women of shorter stature and lower body mass are at greater risk of delivering a baby weighing less than 2500 g. Similarly, women with a pre-pregnancy BMI below 24.9 are more likely to have an LBW newborn, as they are recommended to gain between 11 to 18 kg during pregnancy to achieve an NBW outcome [50], which can be a challenge for some.

Our findings also emphasize the importance of adopting healthy habits during pregnancy to improve birth weight outcomes. It is important to ensure that mothers have access to perinatal care and follow proper

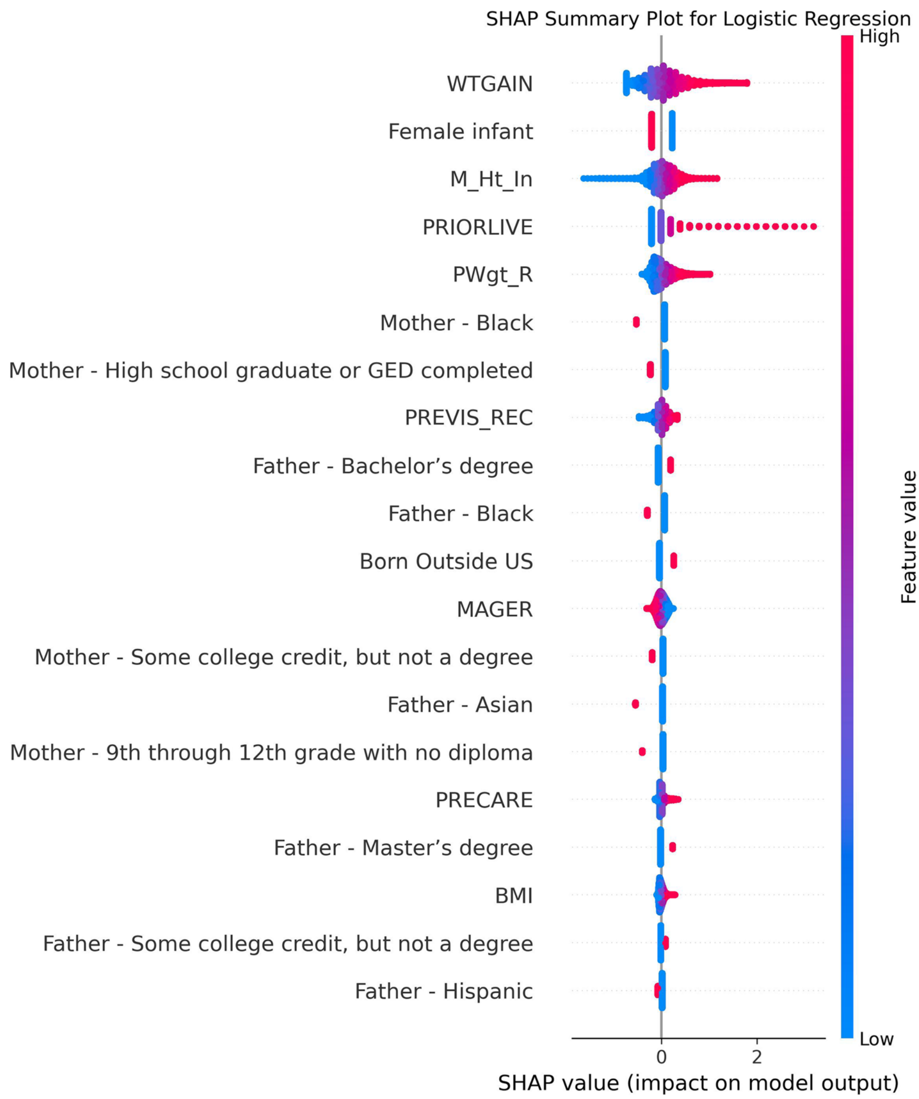

Fig. 15 Top 20 variables ranked by SHAP values for logistic regression

nutrition, which supports healthy weight gain, as these factors strongly contribute to the likelihood of delivering an NBW infant. Other habits, like smoking, should be avoided as it is a strong determinant of LBW. Moreover, pregnancy history needs to also be considered as mothers who have had several successful births are more likely to deliver an NBW newborn. Finally, parental age also matters, as both older mothers and fathers are at an increased risk of having an LBW infant.

One of the most intriguing relationships identified in our study is between maternal height, pre-preganncy weight, weight gain during pregnancy, ethnicity, and birth weight (Fig. 14). Given that maternal anthropometric factors (height, weight, BMI) significantly influence birth weight [49], and that newborns from White parents have higher odds of having NBW (see Table 6), the WHO's cut-off for defining LBW (2500 g) may be biased towards the Caucasian population. This bias is because, except for Black parents, White parents have higher average height than other ethnicities in the US [51–54]. This finding aligns with other studies that advocate for a review of the global WHO's cut-off threshold for LBW [55], which was originally established due to the higher risk of mortality for European-descendent newborns weighing less than 2500 g [9]. Therefore, birth weights less than 2500 g for non-white newborns do not necessarily indicate a high-risk condition (see Fig. 18). It is essential also to consider other factors, such as intrauterine growth restriction, maternal health history, and preterm birth [56, 57].

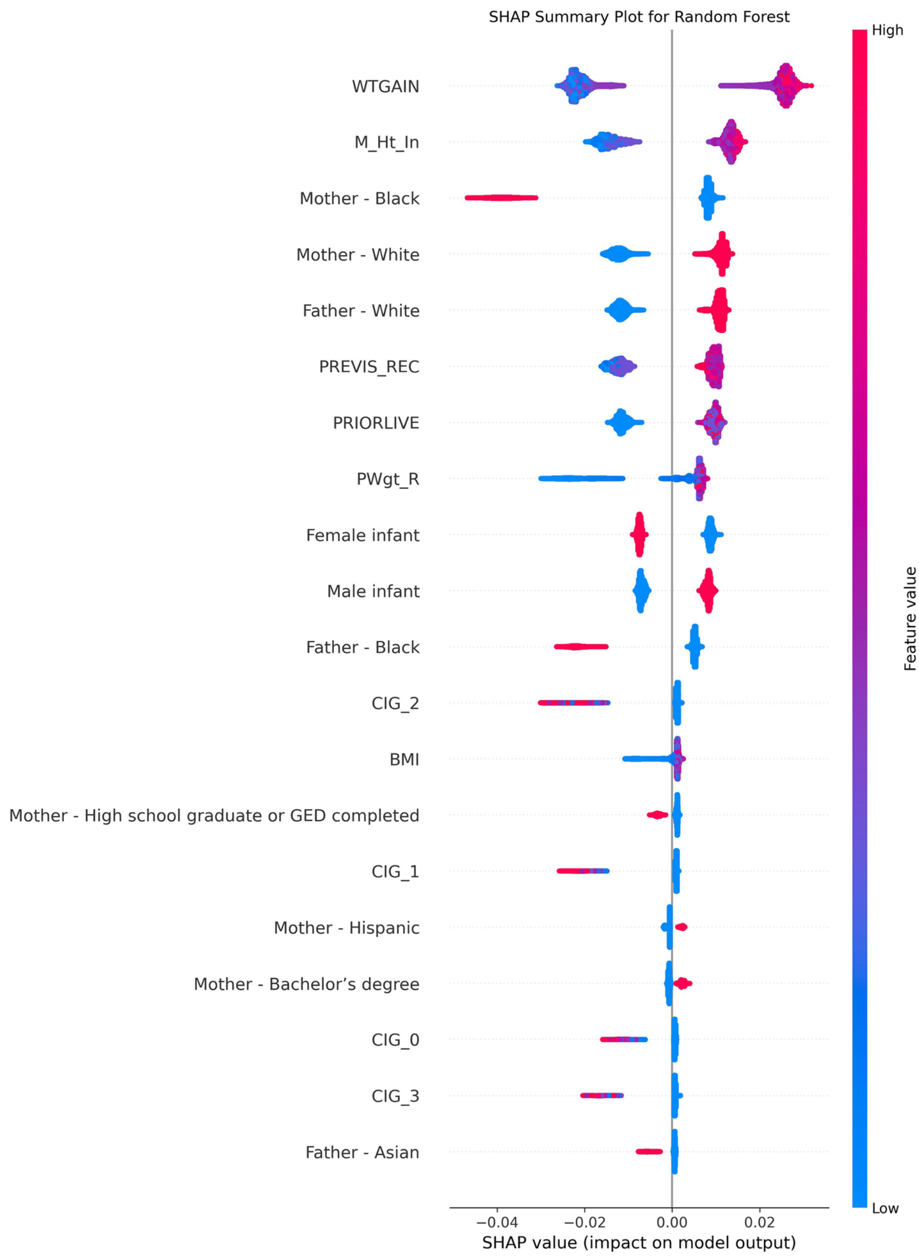

Fig. 16 Top 20 variables ranked by SHAP values for random forest

The high difference between Black and White birth weights seems more related to socioeconomic factors than anthropometrics, as the average heights for both groups are similar (163 cm for females and 178 cm for males [51]). In the US, Black communities have historically been concentrated in low-income areas due to social, economic, and cultural reasons. One contributing factor to this birth weight disparity is nutrition, as Black communities tend to have poorer diets with higher consumption of salt and sugar [58]. Since nutrition is crucial during pregnancy, the lower birth weights in Black newborns compared to their White counterparts may result from this nutritional dissimilarity. Moreover, other socioeconomic factors, such as education and income, play an important role in predicting newborn weight outcomes. Bachelor's graduate parents tend to have newborns with NBW more often than those with lower education levels. Higher years of education can make parents more aware of nutrition and lifestyle choices. Moreover, pregnant women with higher levels of education are more likely to

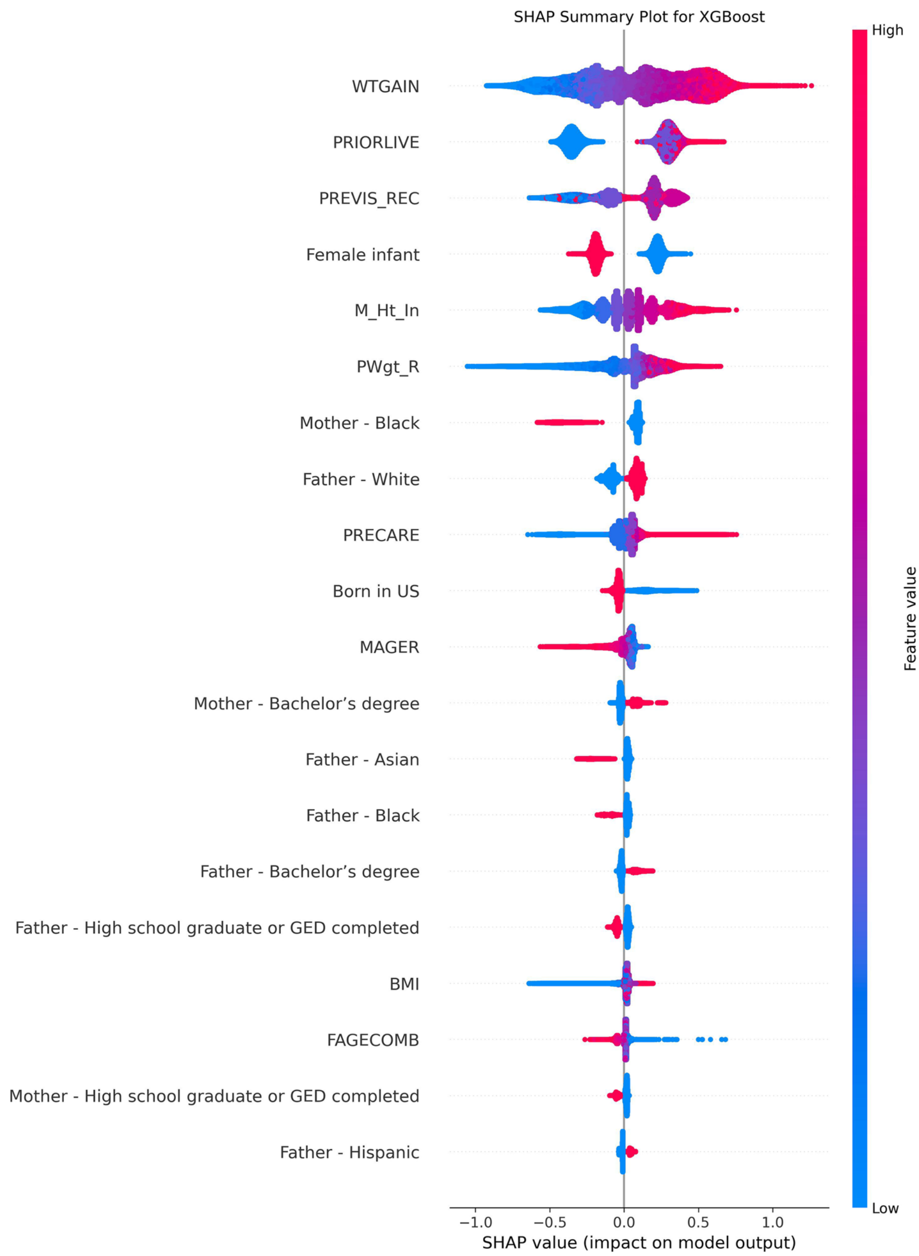

Fig. 17 Top 20 variables ranked by SHAP values for XGBoost

earn higher incomes [59], leading to less stressful pregnancies, better adherence to medical advice, and more regular prenatal checkups.

The identification of weight gain, maternal height, pre-pregnancy weight, and parental ethnicity as crucial factors influencing birth weight outcomes aligns with the findings of Marisaki et al. [7], who emphasized that anthropometric factors are the major factor explaining LBW disparities among ethnicities. However, our study enhances this perspective by indirectly incorporating paternal anthropometrics, noting that paternal ethnicity is correlated with paternal height [51]. Thus, our study provides a more comprehensive understanding of both maternal and paternal factors in predicting LBW outcomes, as paternal height also affects the newborn's anthropometrics. Furthermore, we expand upon the work of Marisaki et al. [7] by showing that when average heights are comparable between ethnicities, such as White and Black parents in the US, disparities in birth weight outcomes are predominantly attributed to other

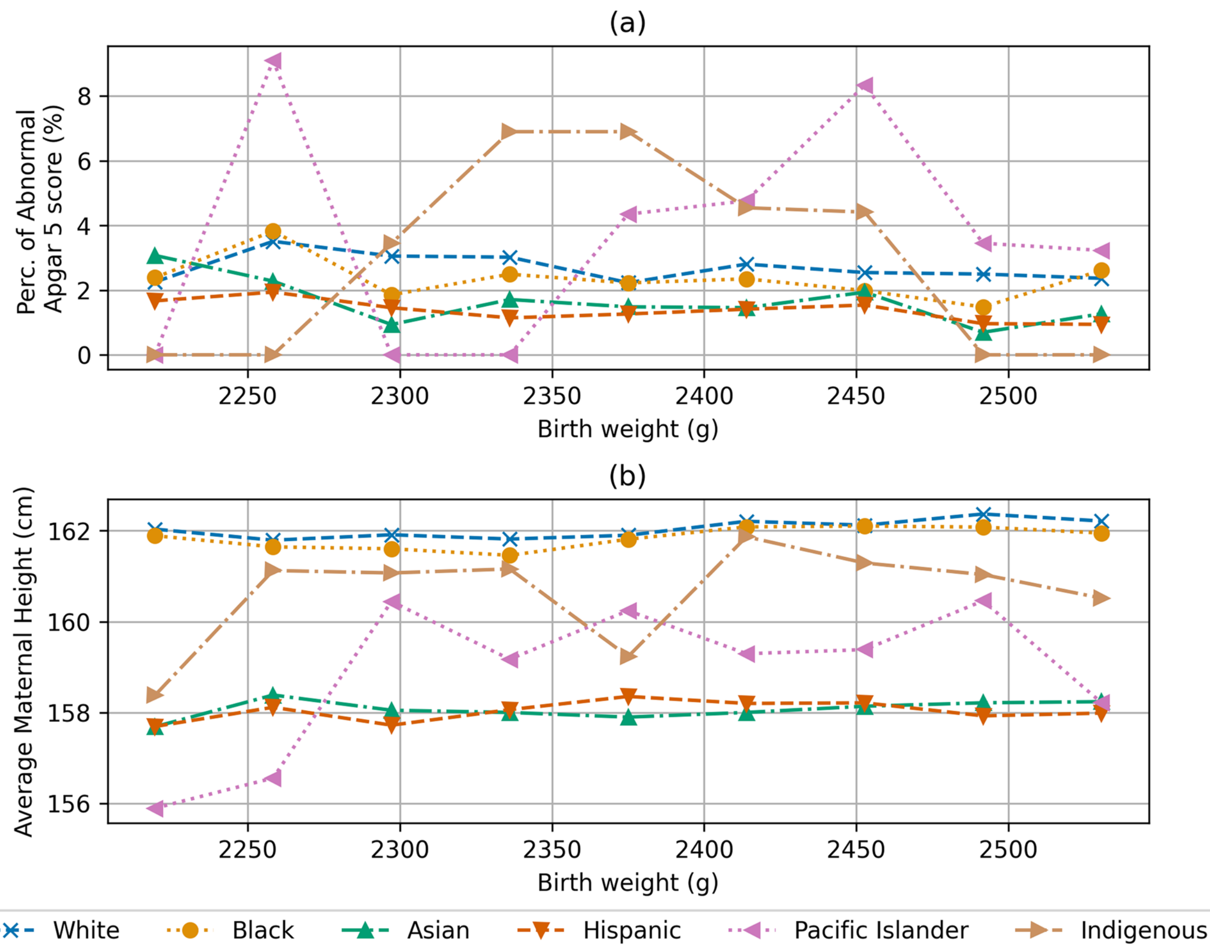

Fig. 18 Birth weight compared to (**a**) newborn well-being, represented by the percentage of abnormal Apgar 5 scores, and (**b**) average maternal height, categorized by ethnic group

factors, particularly access to adequate nutrition. This finding highlights the critical need to consider socio-economic factors alongside anthropometric measures to fully comprehend LBW outcomes.

Strengths and limitations

This is the first study, as far as we know, to use predictive models to analyze various factors and identify the ones most strongly linked to LBW in a nationwide US dataset. Unlike prior studies, we also considered paternal factors in our analysis, demonstrating how parental ethnicity, age, and education level influence birth weight outcomes.

The generalization of our findings was evaluated on an independent test set (see Table 5), yielding an average accuracy of approximately 64% and a macro ROC AUC of nearly 70% for distinguishing between NBW and LBW newborns. This evaluation metric suitably supports the extension of our findings presented in this work. The limitation for achieving a higher accuracy may be attributed to the highly imbalanced dataset, with LBW cases constituting only about 3% of the training data. Nonetheless, our primary objective was to identify critical factors influencing birth weight outcomes rather than solely maximizing accuracy. The comprehensive dataset, which encompasses information from diverse populations across all 50 US states, supports the findings presented in this study.

We note that our analysis was confined to a single dataset collected in 2022. Our rationale was to identify the most relevant predictors using the most current data available from the CDC, thereby reflecting the contemporary situation in the US. This scenario set our study as a cross-sectional analysis, which restricts our ability to conduct longitudinal studies that examine evolving trends between birth weight and parental predictors. Moreover, although recent research suggests that the COVID-19 pandemic did not significantly impact the dynamics of prenatal care visits in the US in

2022 [60], we note that the pandemic may have affected access to perinatal care services for certain households. Future research could explore how the influence of the factors identified in this study has evolved over the past decade concerning birth weight outcomes in the US.

We also recognize that the dataset used in this study lacks factors that may be relevant to determining birth weight outcomes. For instance, key features such as income [61] and paternal factors like height and weight [62] were not included, which could have offered additional insights into the socioeconomic and anthropometric influences on LBW. Future research should address these gaps by incorporating a broader range of datasets and variables to achieve a more comprehensive understanding of the determinants of LBW.

Finally, we note that our analysis identified factors influencing birth weight outcomes based on associations rather than causality. Although machine learning models can capture complex, nonlinear relationships among multiple predictors and the response variable, they do not establish cause-and-effect relationships. Therefore, our study does not imply causality. Instead, the machine learning models identified key anthropometric, ethnic, educational, and pregnancy-related factors that are commonly associated with parents of LBW newborns.

Conclusion

This study analyzed various factors to determine which ones impact the birth weight of newborns in the US the most. To achieve that aim, we used machine learning and deep learning models to create predictive models based on 20 factors, including maternal, parental, socioeconomic, ethnicity, and neonatal factors. Our models showed that certain fixed factors, like maternal height and parents' ethnicity, significantly influence birth weight. Taller and White parents are more likely to have NBW newborns. However, because White parents tend to be taller than parents from other ethnicities, this result should be interpreted with caution. Indeed, as reported by previous studies, the WHO's cut-off for LBW may not be appropriate for non-White ethnicities. Additionally, our findings also indicate that pregnancy-related factors, such as nutrition, smoking habits, and access to perinatal care, are crucial for birth weight. Our findings emphasize the importance of proper nutrition, avoiding smoking, and accessing prenatal care. This is especially crucial for vulnerable communities in the US, such as Black communities, which are statistically significantly more associated with LBW newborns.

Acknowledgements
Not applicable.

Authors' contributions
S.S.D and C.E.V designed the methodology of the study. Both implemented the code and analyze the results. S.S.D. drafted the manuscript, and C.E.V. reviewed and edited. C.E.V. is the supervisor of S.S.D.

Funding
This project was unfunded.

Data availability
Study was conducted using a public available dataset provided by the Centers for Disease Control and Prevention (CDC). The data can be accessed at the following URL: https://www.cdc.gov/nchs/data_access/Vitalstatsonline.htm.

Declarations

Ethics approval and consent to participate
All experiments were performed according to relevant guidelines and regulations (such as the Declaration of Helsinki).

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Applied Computer Science Department, University of Winnipeg, 515 Portage Avenue, Winnipeg R3B 2E9, MB, Canada. [2]Department of Community Health Sciences, Cumming School of Medicine, University of Calgary, 3280 Hospital Drive NW, Calgary T2N 4Z6, AB, Canada.

Received: 26 August 2024 Accepted: 25 November 2024
Published online: 30 November 2024

References

1. Organization WH. UNICEF-WHO low birthweight estimates: levels and trends 2000–2015. World Health Organization; 2019. https://www.unicef.org/reports/UNICEF-WHO-low-birthweight-estimates-2019. Accessed 15 July 2024.
2. Mathewson KJ, Burack JA, Saigal S, Schmidt LA. Tiny Babies Grow Up: The Long-Term Effects of Extremely Low Birth Weight. In: Wazana A, Székely E, Oberlander TF, editors. Prenatal Stress and Child Development. Cham: Springer International Publishing; 2021. pp. 469–490. https://doi.org/10.1007/978-3-030-60159-1_16.
3. Paneth NS. The Problem of Low Birth Weight. Futur Child. 1995;5:19–34. http://www.jstor.org/stable/1602505.
4. Osterman MJK, Hamilton BE, Martin JA, Driscoll AK, Valenzuela CP. Births: Final data for 2022. Natl Vital Stat Rep. 2024;73. Retrieved from National Center for Health Statistics. https://www.cdc.gov/nchs/data/nvsr/nvsr73/nvsr73-02.pdf. Accessed 15 Aug 2024.
5. March of Dimes. Low Birthweight by Race: United States, 2020-2022 Average. 2024. https://www.marchofdimes.org/peristats/data?reg=99&top=4&stop=45 &lev=1 &slev=1 &obj=1. Accessed 15 Aug 2024.
6. Wartko PD, Wong EY, Enquobahrie DA. Maternal birthplace is associated with low birth weight within racial/ethnic groups. Matern Child Health J. 2017;21:1358–66.
7. Morisaki N, Kawachi I, Oken E, Fujiwara T. Social and anthropometric factors explaining racial/ethnical differences in birth weight in the United States. Sci Rep. 2017;7(1):46657.
8. Arabzadeh H, Doosti-Irani A, Kamkari S, Farhadian M, Elyasi E, Mohammadi Y. The maternal factors associated with infant low birth weight: an umbrella review. BMC Pregnancy Childbirth. 2024;24(1):316.
9. McCormick MC. The contribution of low birth weight to infant mortality and childhood morbidity. N Engl J Med. 1985;312(2):82–90.
10. Sharma MK, Kumar D, Huria A, Gupta P. Maternal risk factors of low birth weight in Chandigarh India. Internet J Health. 2009;9:10–2.

11. Shi L, Macinko J, Starfield B, et al. Primary care, infant mortality, and low birth weight in the states of the USA. J Epidemiol Commun Health. 2004;58:374–80.
12. Broere-Brown ZA, Baan E, Schalekamp-Timmermans S, Verburg BO, Jaddoe VW, Steegers EA. Sex-specific differences in fetal and infant growth patterns: a prospective population-based cohort study. Biol Sex Differ. 2016;7:1–9.
13. Bowleg L. When Black+ lesbian+ woman≠ Black lesbian woman: The methodological challenges of qualitative and quantitative intersectionality research. Sex Roles. 2008;59:312–25.
14. Bowleg L. The problem with the phrase women and minorities: intersectionality—an important theoretical framework for public health. Am J Public Health. 2012;102(7):1267–73.
15. Bauer GR. Incorporating intersectionality theory into population health research methodology: challenges and the potential to advance health equity. Soc Sci Med. 2014;110:10–7.
16. Evans CR, Williams DR, Onnela JP, Subramanian S. A multilevel approach to modeling health inequalities at the intersection of multiple social identities. Soc Sci Med. 2018;203:64–73.
17. Evans CR. Adding interactions to models of intersectional health inequalities: comparing multilevel and conventional methods. Soc Sci Med. 2019;221:95–105.
18. Strobl C, Malley J, Tutz G. An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. Psychol Methods. 2009;14(4):323.
19. Stevens LM, Mortazavi BJ, Deo RC, Curtis L, Kao DP. Recommendations for reporting machine learning analyses in clinical research. Circ Cardiovasc Qual Outcomes. 2020;13(10):e006556.
20. National Center for Health Statistics. User Guide to the 2022 Natality Public Use File. 2022. National Center for Health Statistics website. https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/DVS/natality/UserGuide2022.pdf. Accessed 15 Aug 2024.
21. National Center for Health Statistics. Vital statistics online data portal: Birth data files. https://www.cdc.gov/nchs/data_access/Vitalstatsonline.htm. Accessed 21 Aug 2024.
22. Blumenshine PM, Egerter SA, Libet ML, Braveman PA. Father's education: an independent marker of risk for preterm birth. Matern Child Health J. 2011;15:60–7.
23. Mao Y, Zhang C, Wang Y, Meng Y, Chen L, Dennis CL, et al. Association between paternal age and birth weight in preterm and full-term birth: a retrospective study. Front Endocrinol. 2021;12:706369.
24. Casadei K, Kiel J. Anthropometric Measurement. 2024. Updated 2022 Sep 26. StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK537315/. Accessed 15 Aug 2024.
25. Wallace J, Horgan G, Bhattacharya S. Placental weight and efficiency in relation to maternal body mass index and the risk of pregnancy complications in women delivering singleton babies. Placenta. 2012;33(8):611–8.
26. Pölzlberger E, Hartmann B, Hafner E, Stümpflein I, Kirchengast S. Maternal height and pre-pregnancy weight status are associated with fetal growth patterns and newborn size. J Biosoc Sci. 2017;49(3):392–407.
27. Koo YJ, Ryu HM, Yang JH, Lim JH, Lee JE, Kim MY, et al. Pregnancy outcomes according to increasing maternal age. Taiwan J Obstet Gynecol. 2012;51(1):60–5.
28. Reichman NE, Teitler JO. Paternal age as a risk factor for low birthweight. Am J Public Health. 2006;96(5):862–6.
29. Wang X, Zuckerman B, Pearson C, Kaufman G, Chen C, Wang G, et al. Maternal cigarette smoking, metabolic gene polymorphism, and infant birth weight. JAMA. 2002;287(2):195–202.
30. Garces A, Perez W, Harrison MS, Hwang KS, Nolen TL, Goldenberg RL, et al. Association of parity with birthweight and neonatal death in five sites: The Global Network's Maternal Newborn Health Registry study. Reprod Health. 2020;17:1–7.
31. Momeni M, Danaei M, Kermani AJ, Bakhshandeh M, Foroodnia S, Mahmoudabadi Z, Amirzadeh R, Safizadeh H. Prevalence and Risk Factors of Low Birth Weight in the Southeast of Iran. Int J Prev Med. 2017;8(1):12. https://doi.org/10.4103/ijpvm.IJPVM_112_16.
32. Gebrehawerya T, Gebreslasie K, Admasu E, Gebremedhin M. Determinants of low birth weight among mothers who gave birth in Debremarkos referral hospital, Debremarkos town, east Gojam, Amhara region, Ethiopia. Neonat Pediatr Med. 2018;4(1):145.
33. Manniello RL, Farrell PM. Analysis of United States neonatal mortality statistics from 1968 to 1974, with specific reference to changing trends in major causalities. Am J Obstet Gynecol. 1977;129(6):667–74.
34. Quenby S, Gallos ID, Dhillon-Smith RK, Podesek M, Stephenson MD, Fisher J, et al. Miscarriage matters: the epidemiological, physical, psychological, and economic costs of early pregnancy loss. Lancet. 2021;397(10285):1658–67.
35. Gerber-Epstein P, Leichtentritt RD, Benyamini Y. The experience of miscarriage in first pregnancy: the women's voices. Death Stud. 2008;33(1):1–29.
36. Alexander GR, Kotelchuck M. Quantifying the adequacy of prenatal care: a comparison of indices. Public Health Rep. 1996;111(5):408.
37. Conley D, Bennett NG. Race and the inheritance of low birth weight. Soc Biol. 2000;47(1–2):77–93.
38. Zephyrin, L, Seervai, S, Lewis, C, Katon, JG. Community-Based Models to Improve Maternal Health Outcomes and Promote Health Equity. The Commonwealth Fund; 2021. https://www.commonwealthfund.org/publications/issue-briefs/2021/mar/community-models-improve-maternaloutcomes-equity. Accessed 15 Aug 2024.
39. Lebron CN, Mitsdarffer M, Parra A, Chavez JV, Behar-Zusman V. Latinas and Maternal and Child Health: Research, Policy, and Representation. Matern Child Health J. 2023. https://doi.org/10.1007/s10995-023-03662-z.
40. Spinillo A, Capuzzo E, Piazzi G, Baltaro F, Stronati M, Ometto A. Significance of low birthweight for gestational age among very preterm infants. BJOG: Int J Obstet Gynaecol. 1997;104(6):668–73.
41. Armstrong B, Nolin A, McDonald A. Work in pregnancy and birth weight for gestational age. Occup Environ Med. 1989;46(3):196–9.
42. Velaphi S, Mokhachane M, Mphahlele R, Beckh-Arnold E, Kuwanda M, Cooper P. Survival of very-low-birth-weight infants according to birth weight and gestational age in a public hospital. S Afr Med J. 2005;95(7):504–9.
43. Tsai LY, Chen YL, Tsou KI, Mu SC, Group TPIDCS, et al. The impact of small-for-gestational-age on neonatal outcome among very-low-birth-weight infants. Pediatr Neonatol. 2015;56(2):101–7.
44. Hothorn T, Hornik K, Zeileis A. Unbiased recursive partitioning: a conditional inference framework. J Comput Graph Stat. 2006;15(3):651–74.
45. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gómez AN, Kaiser Ł, Polosukhin I. Attention is all you need. Advances in Neural Information Processing Systems: Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS 2017). Long Beach, CA, USA; 2017.
46. Molnar C. 8.1 Partial Dependence Plot (PDP) | Interpretable Machine Learning. 2024. https://christophm.github.io/interpretable-ml-book/pdp.html. Accessed 15 Aug 2024.
47. Fawcett T. An introduction to ROC analysis. Pattern Recogn Lett. 2006;27(8):861–74.
48. Patra S, Sarangi G. Association between maternal anthropometry and birth outcome. J Pediatr Assoc India. 2017;6(2):85–94.
49. Devaki G, Shobha R. Maternal anthropometry and low birth weight: a review. Biomed Pharmacol J. 2018;11(2):815–20.
50. Cunningham FG, Leveno KJ, Bloom SL, Spong CY, Dashe JS, Hoffman BL, et al. Williams Obstetrics. 24th ed. New York: McGraw-Hill; 2014.
51. Komlos J, Baur M. From the tallest to (one of) the fattest: the enigmatic fate of the American population in the 20th century. Econ Hum Biol. 2004;2(1):57–74.
52. Denney JT, Krueger PM, Rogers RG, Boardman JD. Race/ethnic and sex differentials in body mass among US adults. Ethn Dis. 2004;14(3):389–98.
53. Silva AM, Shen W, Heo M, Gallagher D, Wang Z, Sardinha LB, et al. Ethnicity-related skeletal muscle differences across the lifespan. Am J Hum Biol: Off J Hum Biol Assoc. 2010;22(1):76–82.
54. Yin L, Annett-Hitchcock K. Comparison of body measurements between Chinese and U.S. females. The Journal of The Textile Institute. 2019;110(12):1716–24. https://doi.org/10.1080/00405000.2019.1617531.
55. Lucas M. Low birth weight–the less than 2500g cut-off: is it applicable to Sri Lanka? Sri Lanka J Perinat Med. 2023;4(2):6-17. https://doi.org/10.4038/sljpm.v4i2.70.
56. Valderrama CE, Ketabi N, Marzbanrad F, Rohloff P, Clifford GD. A review of fetal cardiac monitoring, with a focus on low-and middle-income countries. Physiol Meas. 2020;41(11):11TR01.

57. Valderrama CE, Marzbanrad F, Hall-Clifford R, Rohloff P, Clifford GD. A proxy for detecting IUGR based on gestational age estimation in a Guatemalan rural population. Front Artif Intell. 2020;3:56.
58. Stephenson BJK, Willett WC. Racial and ethnic heterogeneity in diets of low-income adult females in the United States: results from National Health and Nutrition Examination Surveys from 2011 to 2018. Am J Clin Nutr. 2023;117(3):625–34.
59. Barrett H, Browne A. Health, hygiene and maternal education: Evidence from The Gambia. Soc Sci Med. 1996;43(11):1579–90.
60. Osterman MJ, Hamilton BE, Martin JA, Driscoll AK, Valenzuela CP. Births: Final Data for 2022. Natl Vital Stat Rep: Cent Dis Control Prev Natl Cent Health Stat Natl Vital Stat Syst. 2024;73(2):1–56.
61. Aregay M, Lawson AB, Faes C, Kirby RS, Carroll R, Watjou K. Impact of Income on Small Area Low Birth Weight Incidence Using Multiscale Models. AIMS Public Health. 2015;2:667–680. Epub 2015 Oct 10. PMID: 27398390; PMCID: PMC4936536. https://doi.org/10.3934/publichealth.2015.4.667.
62. Griffiths LJ, Dezateux C, Cole TJ, et al. Differential parental weight and height contributions to offspring birthweight and weight gain in infancy. Int J Epidemiol. 2007;36(1):104–7. https://doi.org/10.1093/ije/dyl210.

Publisher's Note