

# Predicting abnormal birth weight and identifying its determinants using machine learning in the Hararghe Health and Demographic Surveillance System, Ethiopia

**Sington Abdeta**

singtonabdeta128@gmail.com

Haramaya University

**Ousmane Diop**

The Institute for Health Research, Epidemiological Surveillance and Training

**Steve Cygu**

African Population and Health Research Center

**Aboubacry Drame**

Ministry of Health

**Reinpeter Momanyi**

African Population and Health Research Center

**Belayneh Endalamaw**

University of Gondar

**Mulugeta Tadele**

Armauer Hansen Research Institute

**Yordanos Sintayehu**

Armauer Hansen Research Institute

**Miranda Barasa**

African Population and Health Research Center

**Mirkuzie Woldie**

Fenot Associates

**Tsinuel Girma**

Fenot Associates

**Rosa Tsegaye**

Armauer Hansen Research Institute

**Agnes Kiragga**

African Population and Health Research Center

**Merga Deresa**

Haramaya University

**Bethlehem Adnew**

Armauer Hansen Research Institute

**Rawleigh Howe**

Armauer Hansen Research Institute

**Alemseged Abdisa**

Armauer Hansen Research Institute

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## comment

**Keywords:** Prediction, Machine learning, abnormal birth weight, determinants, Hararghe HDSS, Ethiopia

**Posted Date:** March 31st, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-9226614/v1>

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**Additional Declarations:** No competing interests reported.

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**Version of Record:** A version of this preprint was published at BMC Public Health on June 30th, 2026.

See the published version at <https://doi.org/10.1186/s12889-026-28135-0>.

# Abstract

## Background

Birth weight is a reliable measure of intrauterine growth and an important predictor of the newborn's survival, growth, and development. Globally, millions of babies (15.5% for low birth weight and 10% for macrosomia of live births) are born with abnormal birth weight, the majority of whom are in sub-Saharan Africa. Ethiopia is no exception. This study employed a machine learning method using data from the Hararghe health and Demographic Surveillance System, which produced a strong predictive performance in identifying the complex and non-linear relations of factors affecting the birth weight of the newborn.

## Methods

The study developed predictive models for abnormal birth weight using data from the Hararghe Health and Demographic Surveillance System, which is a retrospective cross-sectional in nature, collected from 2015 to 2022. All singleton births were included, and those with missing birth weight data were excluded. Six machine learning models identified to be effective from the previous studies were built and compared to identify the best-performing model for abnormal birth weight prediction. Prior observational studies and expert opinion were used to select the candidate features for all models. Synthetic minority oversampling (SMOTE) was used to manage the imbalance in the dataset. The dataset was divided into training (80%) and testing (20%) subsets to ensure independent model evaluation. Hyper-parametric tuning was performed using grid search combined with 10-fold cross-validation to optimize model performance and reduce over-fitting. The area under the curve (AUROC), accuracy, precision, F1-score, and Kappa were determined. Feature importance analysis was done using Shapley Additive explanation (SHAP) values.

## Results

The Descriptive analysis of 11,553 singleton births showed that 10.78% of the newborns had low birth weight (LBW) and 9.28% had high birth weight (HBW). The eXtreme Gradient Boosting (XGBoost) model performed best by achieving an AUC of 0.835, an accuracy of 0.72, a precision of 0.67, an F1-score of 0.63, a recall of 0.54, and a kappa of 0.52 for abnormal birth weight prediction. The feature importance analysis showed that the top predictors for the low birth weight (LBW) include maternal educational status, age at first delivery, and antenatal care (ANC) visit, while high birth weight (HBW) was strongly predicted by antenatal care (ANC) visit, maternal literacy status, age at first delivery, and maternal education.

## Conclusion

Although using machine learning methods for the prediction of abnormal birth weights has yielded promising results that would have a significant public health impact, more research with comprehensive predictors, which are missing in the Health and Demographic Surveillance System (HDSS), is needed to draw a better conclusion.

## Introduction

Intrauterine growth and development are among the most critical and sensitive processes during human development, and any deviations can lead to immediate and long-lasting significant impacts on the newborn [1]. In many developing nations, birth weight is commonly used to evaluate intrauterine growth [2]. An infant's birth weight serves as a reliable measure of intrauterine growth. It acts as a crucial predictor of the newborn's long-term survival, continued growth, and overall physical and psychological development [3].

Low birth weight (LBW) is defined as a birth weight of less than 2500 grams immediately. It is related to factors like poor maternal nutrition during pregnancy, intrauterine infections, and lack of antenatal care visits [1, 4]. High birth weight (HBW) or Macrosomia is defined as a weight of more than 4000 grams, which is often linked to maternal obesity, pregnancy beyond 39 weeks, and changes in the mother's lifestyle during pregnancy [5]. Newborns who weigh 2500 to 4000 grams just after delivery are considered to have a normal birth weight [6, 7].

The World Health Organization (WHO) estimates that globally, out of 139 million live births, more than 20 million babies with lower than normal birth weight are born each year, constituting 15.5% of all live births, and of whom nearly 95.6% are in developing countries [8].

Several studies in Sub-Saharan Africa have shown that the region accounts for the majority of LBW cases in the world. Socio-demographic risk factors, including young maternal age, primiparity, low educational level, and poor maternal nutritional status both before and during pregnancy, significantly contribute to low birth weight [9, 10]. Additionally, interventions such as focused antenatal care and nutritional counseling during the prenatal and perinatal periods are essential to prevent LBW [11]. On the other hand, few studies have shown that multiparity and maternal obesity are associated with high birth weight [12, 13].

In Ethiopia, despite ongoing maternal and child health interventions, abnormal birth weight (LBW and Macrosomia) remains a major public health problem. The country is among the nations with a high neonatal mortality due to factors associated with abnormal birth weight, especially LBW, which are one of the critical issues that cause newborns to be susceptible to short-term and long-term health consequences and mortality [14].

Despite the reports that abnormal birth weight accounts for perinatal morbidity and mortality, and with the extensive studies in developed countries, fewer studies in the Sub-Saharan African setting have focused on studying risk factors contributing to LBW as well as HBW. The previously existing studies

also applied the conventional statistical methods, which often struggle to capture the complex, non-linear relationships between maternal, fetal, and environmental factors that influence birth weight. The identification and relative contribution of modifiable risk factors of abnormal birth weight may help to redirect interventional priorities of healthcare professionals, families, and policymakers to improve birth outcomes in resource-limited settings. With the growing availability of routine health and demographic surveillance data in Ethiopia, there is a unique opportunity to use modern machine learning techniques for the prediction of abnormal birth weight. Hence, this study aims to identify and prioritize risk factors predicting abnormal birth weight of newborns in Hararghe Health and Demographic Surveillance System, Ethiopia.

## Methods and Materials

Community-based retrospective cross-sectional data extracted from the Hararghe Health and Demographic Surveillance System (HDSS) under Haramaya University were used for this specific study. The Hararghe HDSS was established in 2007 to collect data on population health, demographic events, and related factors to inform evidence-based public health research, policy, and interventions in Ethiopia. It has three HDSS sites: Harar HDSS, Kersa HDSS, and Haramaya HDSS. In the Hararghe HDSS, data are collected through face-to-face interviews using the Open Data Kit (ODK) application, focusing on major variables such as socio-demographic characteristics, birth, death, and other health determinants. The study population includes all singleton live births recorded in the Hararghe HDSS during the study period (2015–2022). The outcome variable is abnormal birth weight classified as low LBW or HBW, and the features include socio-demographic, maternal, and fetal factors.

The description of variables used in the study, which includes key maternal, neonatal, and household-level characteristics that are expected to influence birth weight, is provided in the table below (Table 1). The selection of features was guided by expert opinion and informed by evidence from previous observational studies and ML-based research on child health.

Table 1

Concise description of features used in the study for the prediction of ABW in Hararghe HDSS, Ethiopia, from 2015 to 2017 (n = 11553).

| S.N | Name of a feature                 | Description                                                                 |
|-----|-----------------------------------|-----------------------------------------------------------------------------|
| 1   | C_gender                          | Gender of the fetus                                                         |
| 2   | Occupation_2                      | Indicates the occupation of the mother or the guardian                      |
| 3   | literacy                          | Indicates the literacy status of the mother                                 |
| 4   | gradecomp                         | The highest grade completed by the mother                                   |
| 5   | ageatbirth                        | Age of the mother at the birth of the current child                         |
| 6   | Mother_ageatfirstdelivery         | Age of the mother at the first child's birth                                |
| 7   | Attended_anc                      | Indicates whether the patient has attended at least one ANC visit or not    |
| 8   | Preg_duration                     | Gestational age of the mother for the current child                         |
| 9   | Gravidity                         | Total number of pregnancies the mother has had                              |
| 10  | Preceding-birth outcome           | indicates whether the preceding child is alive, stillborn, or a miscarriage |
| 11  | total_number_children_still_alive | Total number of children born to the mother before the current child        |
| 12  | Wealth index                      | Wealth index of the household                                               |

## Data Extraction and Preprocessing

A total of 13,323 live births initially met the inclusion criteria and were selected. 1,770 newborns with missing birth weight data were excluded, leaving 11,553 observations in the final sample. Important data sets, including birth weight, maternal, environmental, and other neonatal factors registered between 2015 and 2022, were extracted from the Hararghe HDSS database. The raw data, obtained from the Hararghe HDSS database, were first cleaned and preprocessed using the No-Code Codex Platform (<https://doi.org/10.2196/preprints.67836>) developed by the African Population and Health Research Center (APHRC). The platform automates many of the data pre-processing and analysis efforts. Data preprocessing, which involved handling missing values with an appropriate method for each data component and encoding categorical variables, was performed.

Feature engineering included re-categorizing birth weight into LBW, Normal, and HBW. Mother's age at first birth and age at first delivery were recoded into four categories (teenager, young adult, adult, and senior adult). Gravidity was also categorized into three groups (primigravida, multigravida, and grand multigravida). Similarly, the total number of children was categorized into three groups (few (1–3), moderate (4–6), and many (> 6)). Most of the data preprocessing was automated by the platform. Prior

observational and ML-based studies and expert opinion were used to select the candidate features for all models.

## Data Analysis

An initial exploratory data analysis was conducted to understand variable distributions and relationships. The dataset was divided into training and testing sets with an 80% and 20% split, respectively. Six supervised machine learning algorithms, such as the Random Forest classifier, XGBoost classifier, LASSO, Ridge, K-Nearest Neighbor (KNN), and Multinomial logistic regression, and an ensemble of them were developed and compared. Hyper-parameter tuning combined with 10-fold cross-validation was performed to ensure reliable performance estimates and minimize over-fitting.

An automated Grid search was conducted to optimize the hyperparameters of each applied machine learning model. The synthetic minority over-sampling (SMOTE) technique was used to maintain balanced proportions of low birth weight (LBW), normal, and high birth weight (HBW) cases. The models' performance was evaluated using metrics such as Accuracy, Precision, F1-score, kappa, and Area under the ROC Curve (AUC-ROC). Precision reflects the percentage of the model's "positive" predictions that were correct. The F1 score is the harmonic mean of precision and recall, so optimizing it improves both metrics simultaneously. Therefore, researchers often choose the F1 score to evaluate their models instead of accuracy [15]. We selected AUROC as our primary performance metric because it is a widely used measure to assess the effectiveness of machine learning models in predicting outcomes.

Model interpretability was evaluated by SHAP values, which quantify how the model classifies the birth weights as LBW, normal, or HBW. It provides a consistent explanation by computing each feature's contribution to a specific predicted class. We evaluated SHAP summary tools and feature-specific SHAP value plots to understand the cumulative and feature-specific effects of the variables.

## Results

Of the 11,553 live singleton births, 53.03% (6,127) were male. 10.78% (1,245) of newborns had HBW, and 9.28% (1,073) had LBW, while the remainder had normal birth weight. Male newborns were more likely to be high birth weight or macrosomia (711, 11.6%) than female newborns (534, 9.8%), whereas female newborns were slightly more likely to be low birth weight (560, 10.3%) than male newborns (513, 8.4%). 627 (15.2%) of high birth weight babies were born to mothers who could read and write, significantly more than the 616 (8.3%) low birth weight babies born to mothers who could neither read nor write.

Unlike term births, which were primarily of normal weight (8,904, 80.5%). Multigravida mothers had 649 (11.6%) high birth weight deliveries, compared with 206 (11.8%) primigravida and 390 (9.3%) grand multigravida. High birth weight was found in 438 (12.3%) of births from wealthy households and 340 (8.6%) from poor households, according to the household wealth index. The complete descriptive summary of the outcome variable and the predictors is presented in the table below (Table 2).

Table 2

The descriptive characteristics of study participants by birth weight category in Hararghe HDSS, Ethiopia, from 2015 to 2022 (n = 11,553)

| Characteristic               | LBW                          | HBW                          | Normal                       | Overall                       | p-value |
|------------------------------|------------------------------|------------------------------|------------------------------|-------------------------------|---------|
|                              | <b>N = 1,073<sup>1</sup></b> | <b>N = 1,245<sup>1</sup></b> | <b>N = 9,235<sup>1</sup></b> | <b>N = 11,553<sup>1</sup></b> |         |
| <b>Child's gender</b>        |                              |                              |                              |                               | < 0.001 |
| Female                       | 560 (10.3)                   | 534 (9.8)                    | 4,332 (79.8)                 | 5,426 (100.0)                 |         |
| Male                         | 513 (8.4)                    | 711 (11.6)                   | 4,903 (80.0)                 | 6,127 (100.0)                 |         |
| <b>Occupation</b>            |                              |                              |                              |                               | < 0.001 |
| Don't have an occupation     | 64 (5.6)                     | 121 (10.6)                   | 954 (83.8)                   | 1,139 (100.0)                 |         |
| Have an occupation           | 1,009 (9.7)                  | 1,124 (10.8)                 | 8,281 (79.5)                 | 10,414 (100.0)                |         |
| <b>Literacy</b>              |                              |                              |                              |                               |         |
| Neither reads nor writes     | 745 (10.1)                   | 616 (8.3)                    | 6,024 (81.6)                 | 7,385 (100.0)                 |         |
| Reads and writes             | 323 (7.8)                    | 627 (15.2)                   | 3180 (77.0)                  | 4130 (100.0)                  |         |
| Only reads                   | 5 (13.2)                     | 2 (5.3)                      | 31 (81.6)                    | 38 (100.0)                    |         |
| <b>Grade completed</b>       |                              |                              |                              |                               | < 0.001 |
| High Level                   | 16 (6.3)                     | 98 (38.3)                    | 142 (55.5)                   | 256 (100.0)                   |         |
| No formal education          | 456 (14.1)                   | 377 (11.7)                   | 2,395 (74.2)                 | 3,228 (100.0)                 |         |
| Primary                      | 259 (8.4)                    | 333 (10.7)                   | 2,506 (80.9)                 | 3,098 (100.0)                 |         |
| Secondary/Preparatory        | 342 (6.9)                    | 437 (8.8)                    | 4,192 (84.3)                 | 4,971 (100.0)                 |         |
| <b>Mother's age at birth</b> |                              |                              |                              |                               | 0.11    |
| Adult                        | 541 (9.5)                    | 636 (11.2)                   | 4,514 (79.3)                 | 5,691 (100.0)                 |         |

| Characteristic                        | LBW                    | HBW                    | Normal                 | Overall                 | p-value |
|---------------------------------------|------------------------|------------------------|------------------------|-------------------------|---------|
|                                       | N = 1,073 <sup>1</sup> | N = 1,245 <sup>1</sup> | N = 9,235 <sup>1</sup> | N = 11,553 <sup>1</sup> |         |
| Senior Adult                          | 252 (9.8)              | 265 (10.3)             | 2,045 (79.8)           | 2,562 (100.0)           |         |
| Teenager                              | 66 (7.5)               | 78 (8.9)               | 731 (83.5)             | 875 (100.0)             |         |
| Young                                 | 214 (8.8)              | 266 (11.0)             | 1,945 (80.2)           | 2,425 (100.0)           |         |
| <b>Mother's age at first delivery</b> |                        |                        |                        |                         |         |
| Adult                                 | 39 (8.4)               | 146 (31.6)             | 277 (60.0)             | 462 (100.0)             |         |
| Senior Adult                          | 1 (7.1)                | 4 (28.6)               | 9 (64.3)               | 14 (100.0)              |         |
| Teenager                              | 813 (9.7)              | 767 (9.2)              | 6,764 (81.1)           | 8,344 (100.0)           |         |
| Young                                 | 220 (8.0)              | 328 (12.0)             | 2,185 (79.9)           | 2,733 (100.0)           |         |
| <b>Attended ANC</b>                   | 484 (8.8)              | 793 (14.4)             | 4,215 (76.7)           | 5,492 (100.0)           | < 0.001 |
| <b>Gestational age</b>                |                        |                        |                        |                         | < 0.001 |
| Post-term                             | 62 (16.9)              | 51 (13.9)              | 254 (69.2)             | 367 (100.0)             |         |
| Pre-term                              | 29 (23.8)              | 16 (13.1)              | 77 (63.1)              | 122 (100.0)             |         |
| Term                                  | 982 (8.9)              | 1,178 (10.6)           | 8,904 (80.5)           | 11,064 (100.0)          |         |
| <b>Gravidity</b>                      |                        |                        |                        |                         | < 0.001 |
| Grand Multigravida                    | 455 (10.8)             | 390 (9.3)              | 3,354 (79.9)           | 4,199 (100.0)           |         |
| Multigravida                          | 474 (8.4)              | 649 (11.6)             | 4,490 (80.0)           | 5,613 (100.0)           |         |
| Primigravida                          | 144 (8.3)              | 206 (11.8)             | 1,391 (79.9)           | 1,741 (100.0)           |         |
| <b>Preceding birth outcome</b>        |                        |                        |                        |                         |         |
| Live birth                            | 920 (9.3)              | 1,041 (10.5)           | 7,920 (80.2)           | 9,881 (100.0)           | 0.010   |

| Characteristic                              | LBW                          | HBW                          | Normal                       | Overall                       | p-value |
|---------------------------------------------|------------------------------|------------------------------|------------------------------|-------------------------------|---------|
|                                             | <b>N = 1,073<sup>1</sup></b> | <b>N = 1,245<sup>1</sup></b> | <b>N = 9,235<sup>1</sup></b> | <b>N = 11,553<sup>1</sup></b> |         |
| Miscarriage                                 | 85 (7.7)                     | 143 (13.0)                   | 873 (79.3)                   | 1,101 (100.0)                 |         |
| Still birth                                 | 68 (11.9)                    | 61 (10.7)                    | 442 (77.4)                   | 571 (100.0)                   |         |
| <b>Total number of children still alive</b> |                              |                              |                              |                               |         |
| Few                                         | 522 (8.4)                    | 740 (11.9)                   | 4,950 (79.7)                 | 6,212 (100.0)                 | < 0.001 |
| Many                                        | 181 (11.7)                   | 165 (10.6)                   | 1,205 (77.7)                 | 1,551 (100.0)                 |         |
| Moderate                                    | 370 (9.8)                    | 340 (9.0)                    | 3,080 (81.3)                 | 3,790 (100.0)                 |         |
| <b>Wealth index</b>                         |                              |                              |                              |                               |         |
| Average                                     | 426 (10.5)                   | 467 (11.6)                   | 3,148 (77.9)                 | 4,041 (100.0)                 | < 0.001 |
| Poor                                        | 360 (9.1)                    | 340 (8.6)                    | 3,250 (82.3)                 | 3,950 (100.0)                 |         |
| Rich                                        | 287 (8.1)                    | 438 (12.3)                   | 2,837 (79.6)                 | 3,562 (100.0)                 |         |

In this study, the model parameters and feature importance were evaluated by comparing the performance of different machine learning algorithms. AUC was computed, and an ROC was generated to identify how the models balance false positive rates and sensitivity. The XGBoost model achieved the best performance with an AUC of 0.83, an accuracy of 0.72, a precision of 0.67, an F1-score of 0.63, a recall of 0.54, and a kappa of 0.52, followed by the Ensemble model with an AUC of 0.81. XGBoost also demonstrated a good discriminatory ability (Fig. 1)

As can be seen in the confusion matrix heatmap below (Fig. 2), the XGBoost model classified birth weight into normal, low, and high categories with moderate accuracy. Normal birth weight is correctly identified in 25% of cases, while 14.9% of low birth weight and 15.9% of high birth weight cases are correctly classified. Some degree of misclassification is evident, particularly where low and high birth weight cases are predicted as normal.

As one can understand from the feature importance plot below (Fig. 3), the top five predictors of LBW are maternal educational status, mother's age at first delivery, ANC attendance, gestational age, and literacy of the mother. Gender of the newborn and wealth index are also among the predictors of LBW.

For HBW (Fig. 4), having ANC follow-up is the strongest predictor, followed by maternal literacy status and age at first delivery. The mother's educational status and the gender of the newborn are next. The number of preceding children currently alive and gravidity also contribute.

The SHAP beeswarm plot below (Fig. 5a) indicates that ANC follow-up status is the most influential predictor, with having an ANC follow-up strongly favoring the HBW and having no ANC follow-up reducing it. Pre-term delivery reduces the probability of HBW, whereas maternal literacy (being able to read and write) favors HBW. The wealth index was also shown to have an effect, with rich households increasing and poor households decreasing the likelihood of HBW. Male gender increases the probability of HBW, while young or teenage age at first delivery and adverse previous pregnancy outcomes, such as stillbirth, are associated with lower predicted HBW.

In the LBW predicting model (Fig. 5b), the most significant risk factor is the mother having no formal education, which strongly shifts the prediction toward a positive LBW outcome. Pre-term pregnancy acts as a major driver for increased risk, while term pregnancy and attending antenatal care (ANC) serve as critical protective factors that lower the probability of LBW. The model also shows that literate mothers with a preparatory level of education have a reduced risk of newborns with low birth weight.

## Discussion

# Performance of the Machine Learning Model

In recent years, healthcare data have been growing rapidly in both quantity and dimension, making machine learning algorithms the preferred approaches for handling these growing data [16]. In this study, a machine learning model was applied to predict abnormal birth weight and to identify important features among newborns in Hararghe HDSS. Our comparison of six supervised ML algorithms showed that the eXtreme Gradient Boosting (XGBoost) model outperformed the others in predicting ABW. XGBoost estimates feature importance using internal importance scores, allowing clear identification of influential predictors. Prior studies that have applied machine learning models to predict ABW have reported encouraging performance. Ranjibar et al. [17] demonstrated that an XGBoost model achieved strong diagnostic metrics, including an accuracy of 0.79, a precision of 0.87, a recall of 0.69, and an F1 score of 0.77. Similarly, Desiani et al. [18] reported excellent performance of the naïve Bayes model, with an accuracy of 0.85 and a recall of 0.72. Despite these favorable results, both studies were limited by a small sample size. The XGBoost model achieved the highest performance with an Area under the Curve (AUC) of 0.83, an accuracy of 0.72, a precision of 0.67, an F1-score of 0.63, and a kappa of 0.52. This supports the study's goal of assessing how well ML models can predict birth weight. This finding aligns with previous literature suggesting that ML algorithms are the preferred methods for handling the rapidly growing quantity and dimension of healthcare data, and is relatively higher than the performance of the same model in the study done by [19], which had an AUC of 0.79.

# Feature Importance and Factors Associated with Abnormal Birth Weight

The SHAP beeswarm analysis provides a granular view of how socio-demographic, maternal and fetal factors drive the model's predictions for abnormal birth weight. The strength of the XGBoost model enabled a nuanced exploration of the predictors of ABW, addressing the second research question regarding the main factors that determine ABW. The analysis clearly revealed the factors that influence each abnormal birth weight category.

The model identifies maternal education as a strong predictor of low birth weight, with having no formal education shifting the prediction towards a positive LBW outcome. Other studies revealed, in regions like sub-Saharan Africa and South Asia, the lack of formal education emerges as the most significant risk factor for LBW [20–22]. This finding is in line with a study conducted in Ethiopia, which ranks maternal education among the top features for predicting low birth weight newborns [21]. This can be explained by the idea that education serves as a proxy for nutritional knowledge, which is that women with lower levels of education less frequently access micronutrient supplementation and sufficient calorie intake needed for healthy fetal development during pregnancy[21, 23].

The wealth index of the household is also revealed to have an effect on birth weight, with a wealth status favoring HBW and the poor one positively predicting LBW. This reflects a nutritional transition observed in developing economies where increased socioeconomic status is associated with more sedentary lifestyles [24, 25]. In machine learning studies utilizing Gradient Boosting and Random Forest on datasets from public hospitals in Ethiopia, researchers have highlighted that as household income increases, the risk of metabolic complications such as gestational diabetes also rises, pushing SHAP values toward the HBW end [26]. Antenatal Care (ANC) showed contrasting effects on the prediction of LBW and macrosomia. The protective effect of ANC against LBW is a standard clinical expectation, where regular visits allow for the early detection of intrauterine growth restriction and are probably due to the nutritional supplements and the identification of other modifiable risk factors, as revealed by [27, 28]. However, the finding that ANC is associated with an increased risk of HBW could describe that nutritional counselling and supplementations during ANC visits generally increase the birth weight and, in some cases, can lead to fetal overgrowth [29]. Macrosomia can also be linked to the metabolic and clinical factors identified during ANC follow-up, making ANC a screening modality rather than a cause of macrosomia [30].

The findings from this study, as evidenced by many other previous studies, showed that gestational age and fetal sex are among the top predictors of abnormal birth weight. Preterm birth was identified as a major contributor to low birth weight. [31] also revealed consistent results and stated that the finding is biologically plausible, as the third trimester represents a critical period for accelerated fetal growth, tissue maturation, and fat deposition. When pregnancy is shortened, the fetus is deprived of this vital growth window, resulting in reduced birth weight [32]. In contrast, the model identified the male gender as a significant predictor of HBW, a "sexual dimorphism" in fetal growth. This finding is roughly in line

with [33]. This is because male fetuses typically exhibit different placental growth strategies and higher metabolic rates, leading to increased weight at birth [19, 34]. Furthermore, the models show that young and teenage maternal ages [21] and adverse previous outcomes (miscarriage) increase the likelihood of LBW while negatively predicting macrosomia. This is consistent with the finding of Akhtar et al. (2025), which could reflect physiological constraints or uterine "depletion" that limits growth potential in subsequent pregnancies [35].

## Limitations of the study

Although we utilized a large dataset encompassing several maternal and neonatal factors, key variables such as maternal BMI, maternal comorbidities, maternal nutritional status during pregnancy, and the presence of pregnancy complications are missing in this HDSS dataset, which usually doesn't capture sufficient detail and relevant information regarding pregnancy or other medical conditions that are useful to predict birth outcomes. Due to this, these variables were not included in our feature selection, which limits the ability of the model to capture the full picture of the risk factors of abnormal birth weight. Machine learning models themselves have limitations in their inability to provide a quantitative estimate of uncertainty.

## Conclusion and Future Direction

The application of the XGBoost model on the Hararghe HDSS data showed how machine learning can effectively predict abnormal birth weights in resource-limited settings. The model not only offers a robust prediction tool (AUC = 0.83) but also provides important epidemiological insights by identifying the factors that influence LBW and HBW. Future research should incorporate important datasets, such as maternal BMI, maternal comorbidities, maternal nutritional status, and behavioral activities of the mother during pregnancy, to increase the model's public health value by producing a more robust predictive tool.

## Declarations

### Ethics approval and consent to participate

This study complied with the Declaration of Helsinki

### Consent for publication

Not applicable

### Competing interests

The authors declare that there is no competing interest.

# Funding

There was no direct funding for this study.

# Author Contribution

SA extracted the data and drafted the introduction, methodology, and discussion sections. MD and BE provided constructive feedback throughout the development of this manuscript. AD, OD, and RM led the results development. SC supported all stages of the work, including data analysis, results preparation, and drafting the discussion. The AHRI and FENOT teams also made substantial contributions to the development of this manuscript through critical and constructive comments from the first draft through to the final version. All authors reviewed, edited, and approved the final manuscript.

# Data Availability

The dataset used for this study will be accessed upon a reasonable request.

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# Figures

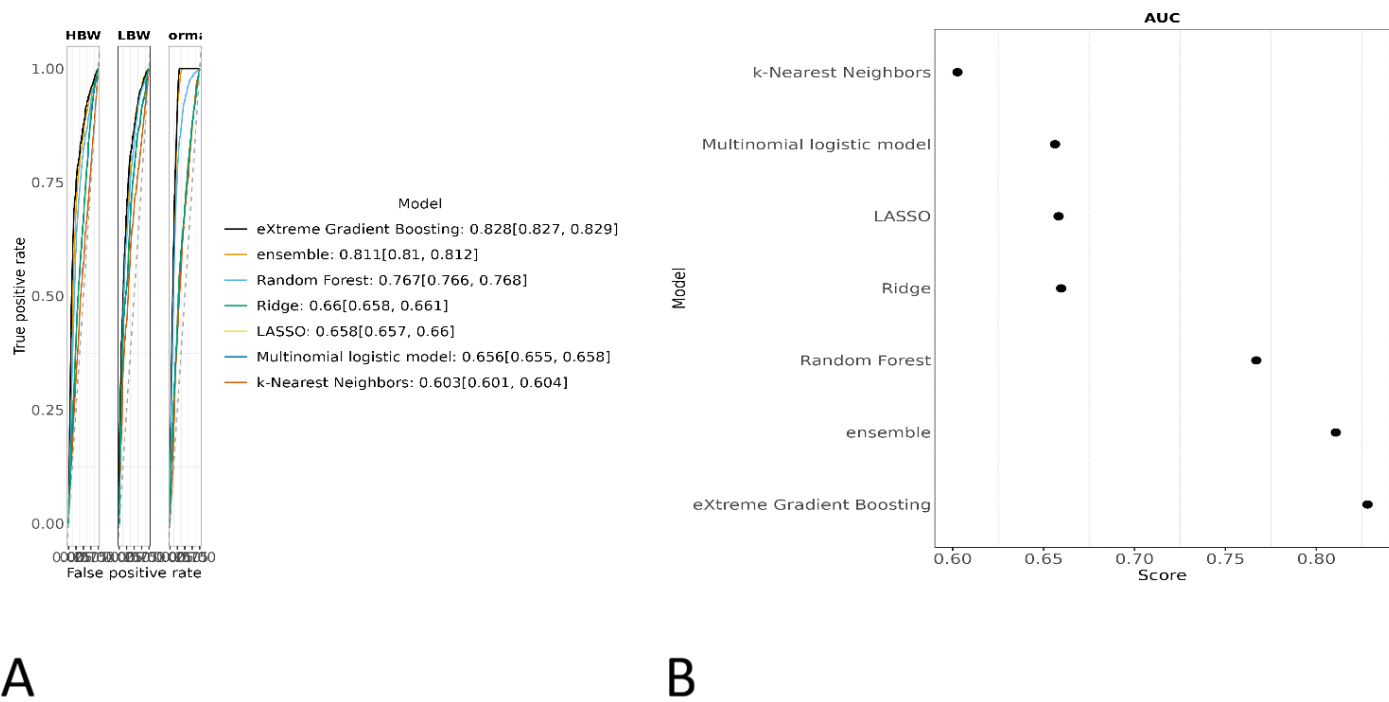


Figure 1

a: The ROC of the models for the prediction of abnormal birth weight from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).

b: AUC of the models for the prediction of abnormal birth weight from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).

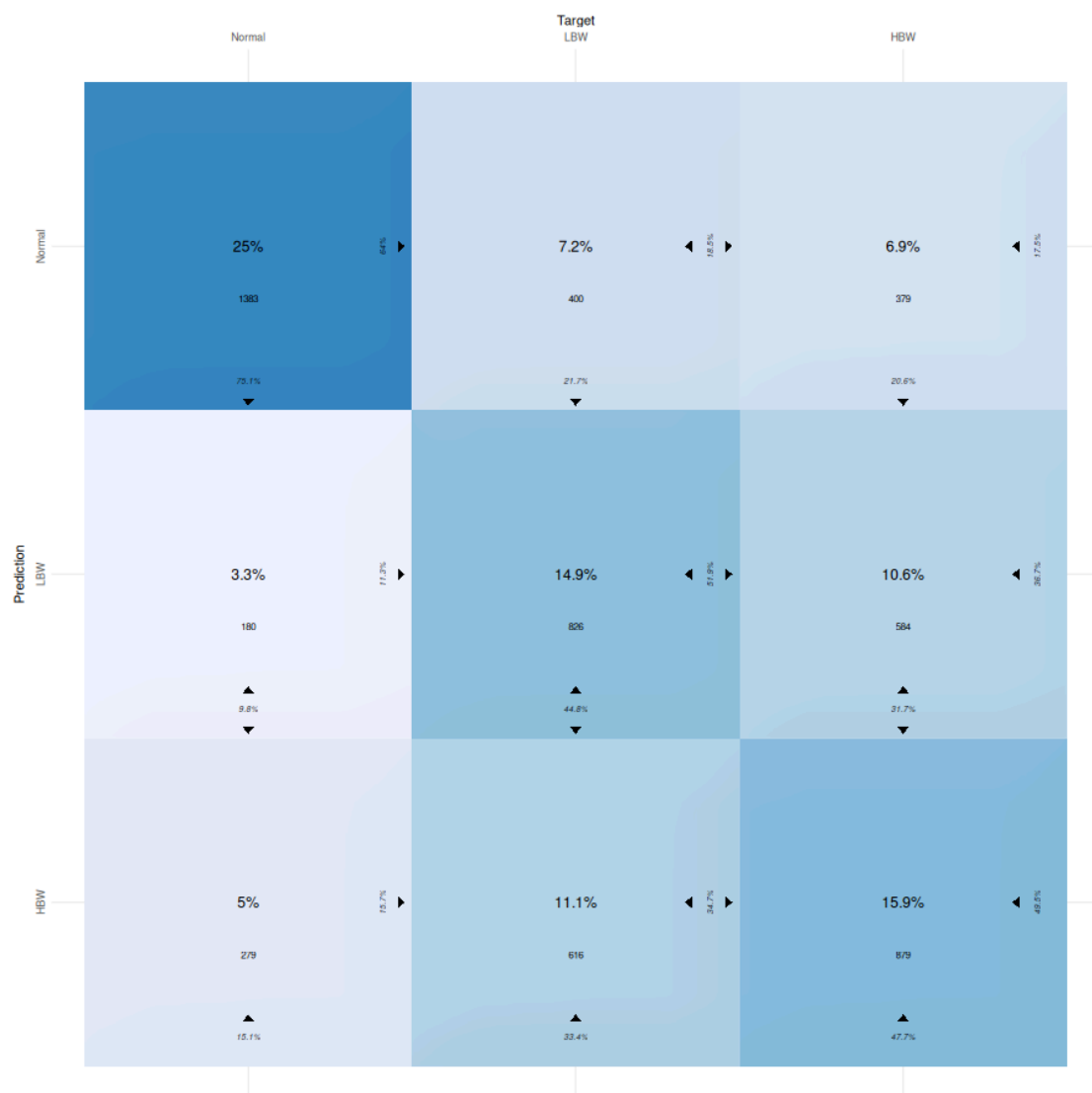


**Figure 2**

Confusion matrix for the prediction of abnormal birth weight from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).

Determinants of Low BW

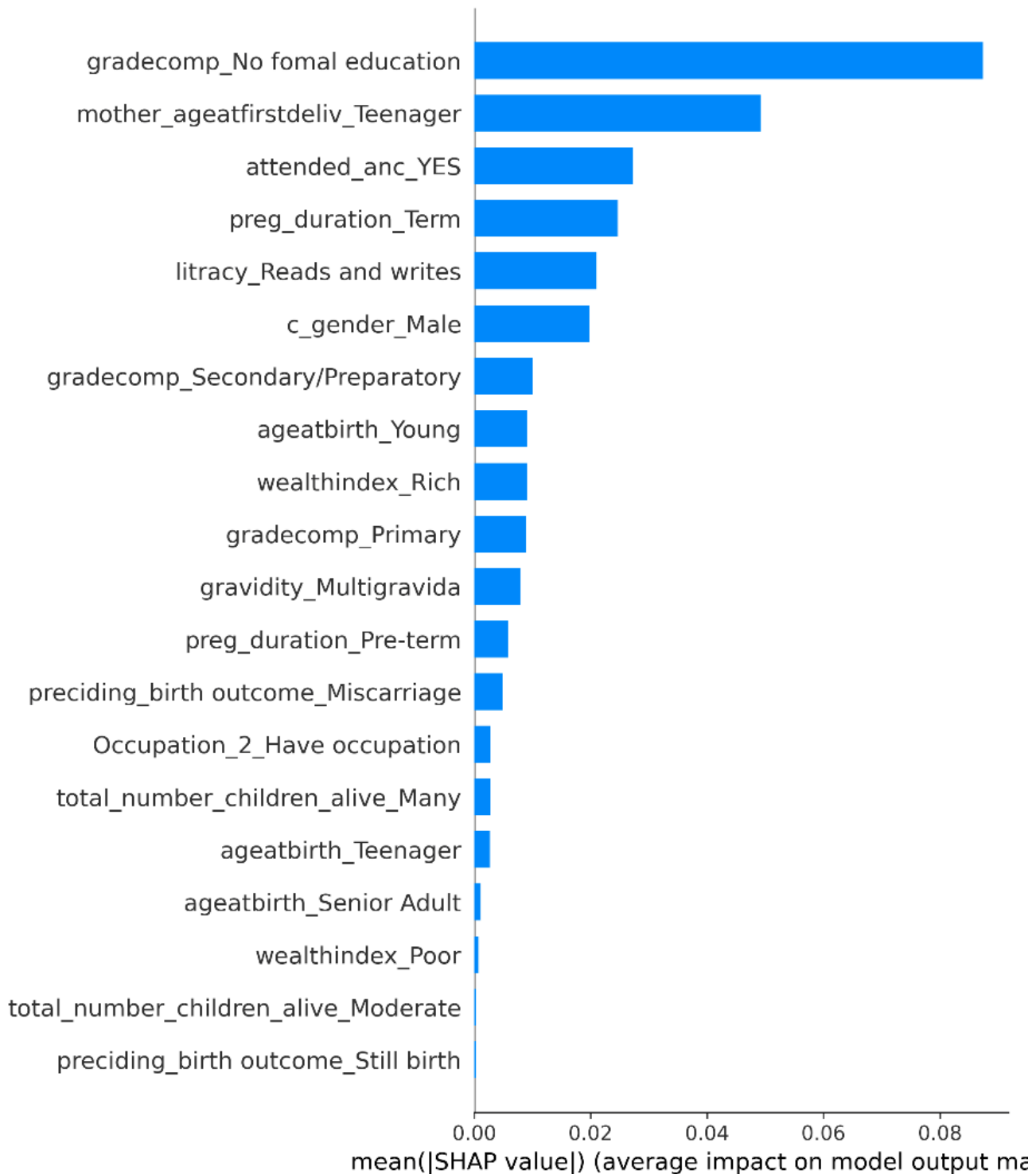


**Figure 3**

Feature importance analysis for predicting low birth weight from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).

Determinants of High BW

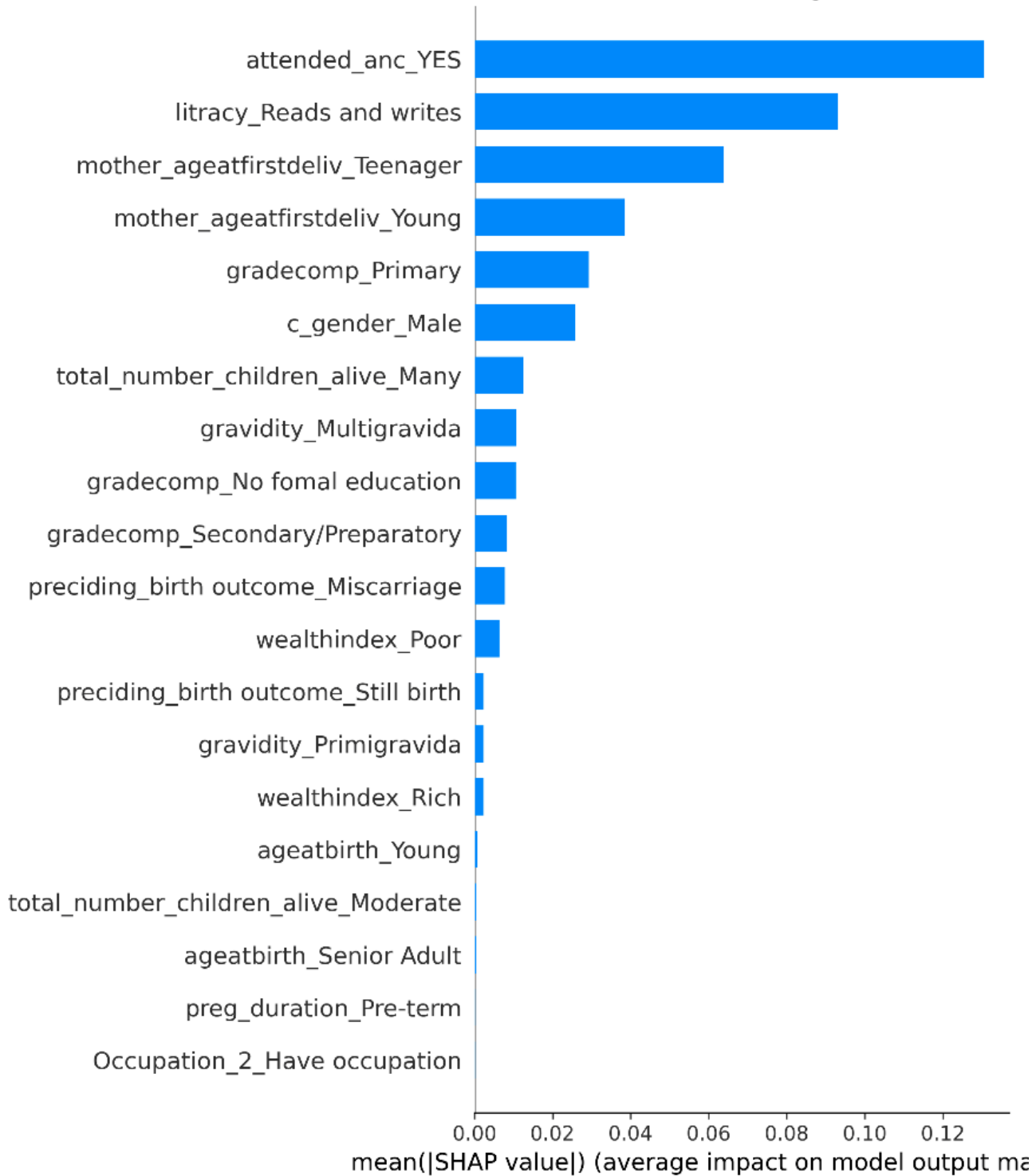
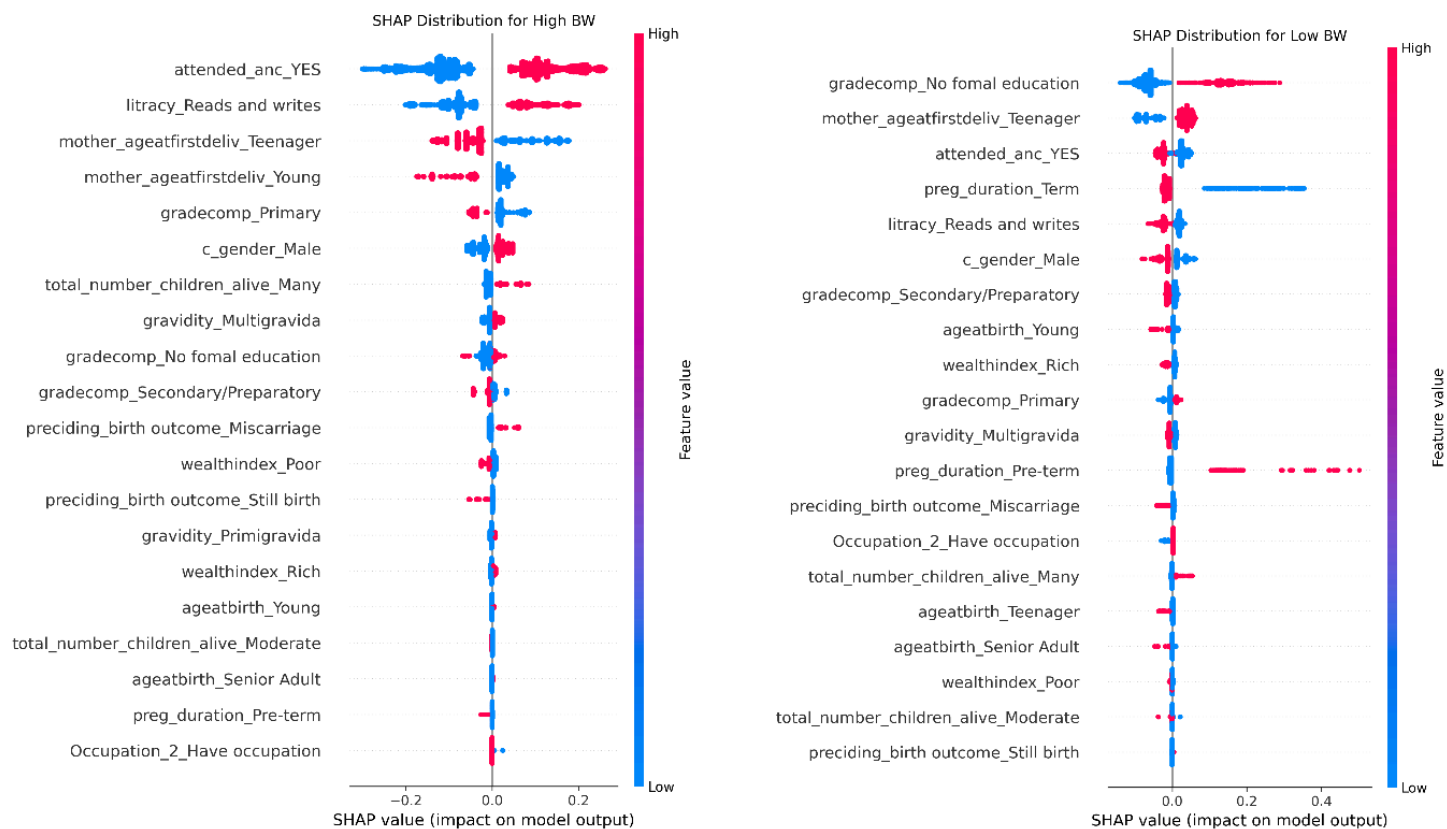


**Figure 4**

Feature importance analysis for predicting high birth weight from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).



A

B

**Figure 5**

a: Feature importance analysis of the XGBoost model for HBW prediction from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).

b: Feature importance analysis of the XGBoost model for LBW prediction from 2015 to 2017 in the Hararghe HDSS, Ethiopia, (n= 11553).