Clinical Epidemiology and Global Health 41 (2026) 102451

Contents lists available at ScienceDirect

Clinical Epidemiology and Global Health

journal homepage: www.elsevier.com/locate/cegh

Machine learning approach to early detection of low birth weight among neonates in eastern India

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ARTICLE INFO

Keywords:
Low birth weight
Study-defined VLBW
Artificial neural network
Cross-sectional observational data
Area under curve

ABSTRACT

Background: Low birth weight (LBW), remains a major determinant of infant mortality and morbidity, serves as a critical indicator of maternal health, nutrition, and socioeconomic conditions. Early detection enables targeted interventions in vulnerable rural settings.

Aims: This study applied artificial neural network (ANN)-based models across four domains. Model 1- socio-demographic and economic factors, Model 2 - prenatal conditions and service utilization factors, Model 3- maternal complications and morbidity factors and Model 4- maternal nutritional factors-to identify determinants for early risk prediction of LBW among neonates in rural eastern India.

Methods: Cross-sectional data from 352 pregnant women, encompassing prenatal to postnatal predictive factors, were used to develop four ANN predictive models. Predictor importance was estimated using sensitivity analysis in SPSS v22 (®IBM Inc) Neural Networks. Model performance was evaluated using the area under the curve (AUC), root mean squared error (RMSE) and F1 score. As very few infants met the World Health Organization (WHO)-defined very low birth weight (VLBW) threshold (<1.5 kg), a study-defined VLBW subgroup (<2.2 kg) was adopted solely for analytical stratification.

Results: Model 3 showed best performance, with highest AUC (0.756), and lowest RMSE (0.394). Model 2 demonstrated moderate performance (AUC of 0.716) with F1 scores of 0.677 (study-defined VLBW) and 0.675 (LBW).

Conclusions: Maternal age, hemoglobin level and pre-pregnancy body mass index (BMI) emerged as key predictors of LBW. ANN models demonstrated discriminatory performance within an internal validation framework, offering exploratory insights for early risk prediction. However, external validation using independent datasets is required before broader applicability can be established.

1. Introduction

Low birth weight (LBW) is defined as a birth weight of less than 2500 g (5.5 pounds).[1] The burden of LBW is particularly high in South Asia, where nearly 28% of newborns are affected.[2] Approximately 96.5% of LBW births occur in low and middle-income countries (LMICs), particularly among socio-economically disadvantaged populations.[3] LBW remains a leading determinant of infant mortality and morbidity, influenced by multiple fetal and maternal risk factors including maternal under-nutrition, untreated medical conditions, environmental hazards, and socio-economic deprivation. These factors primarily contribute to adverse birth outcomes, such as pre-term birth (PTB) and LBW.[4]

LBW is not a disease with a single pathophysiological mechanism. Rather, intrauterine growth retardation (IUGR) and preterm birth (PTB), together with a range of maternal and neonatal factors, are considered to be the primary underlying causes of LBW.[2] Consequently, the risk of LBW is associated with several maternal, demographic and socio-economic determinants, including maternal mental and physical health, maternal age at birth, birth order, the number of antenatal care (ANC) visits, maternal smoking habits, education level, lower employment rates, reduced income, area of residence and overall economic status etc. [5–8].

In recent years, the artificial neural network (ANN) technique has emerged as a highly flexible and accurate machine learning (ML) algorithm, widely used for predictive modeling across diverse fields.[9] It has also been applied to predict causes of death and birth outcomes.[10] This

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https://doi.org/10.1016/j.cegh.2026.102451
Received 10 March 2026; Received in revised form 14 August 2026; Accepted 17 August 2026
Available online 18 August 2026

computational model is inspired by the structural organization of biological neural networks, and is widely acknowledged for its pattern recognition, classification, and prediction abilities.[11]

Hence, this study aims to identify the key determinants of LBW among rural ever-married women of reproductive age (WRA), and to develop and evaluate ANN-based predictive models for early identification of LBW risk among neonates in rural eastern India.

The models were intentionally designed to reflect regional realities, instead of aiming towards broad generalization, thereby exploring regional sensitivity arising from local variations that are often overlooked by overgeneralization. This context-specific approach to predictive modeling may support targeted interventions for high-risk pregnancies in underserved communities across rural eastern India that share comparable demographic, cultural and geographical characteristics. However, as the models were evaluated using internal validation, further external validation using independent datasets is required before establishing broader applicability.

2. Methods

2.1. Study design and participants

This cross-sectional ML-based predictive modeling study, using observational cohort data, was conducted in a vulnerable part of Eastern India, selected for its consistently poor maternal and neonatal outcomes. It has consistently occupied one of the most alarming positions in terms of vulnerable obstetric health outcomes within the region.[12,13] According to national multidimensional poverty index (NMPI) based on the National Family Heath Survey 5,[14] the study area ranked fourth, with 18.27% of the population classified as multidimensionally poor.[15,16] This combination of high obstetric risk and structural deprivation justified its selection as a critical setting for studying LBW.

Inclusion criteria of the cohorts were as follows: (1) singleton pregnancy of ever-married WRA (15-49 years); (2) availability of complete clinical data covering the antenatal, delivery and postnatal periods (PNC). Women with multiple gestations, major fetal congenital anomalies, or incomplete records were excluded from the analytical sample; (3) infants were required to be weighed within 1 h of institutional delivery and within 24 h of home delivery for recording birth weight data.[1,6,17]

A stratified random sampling strategy was employed to ensure an unbiased and representative sample and to reduce sampling variance. Strata were constructed using available district-level demographic and health data with participants randomly selected within each group. This design improved precision and allowed better comparability across subgroups within heterogeneous maternal health populations.

The entire study was based on empirical data, initially comprising 785 women. Out of these, 388 were excluded from the analysis as they were still in their ANC stage at the time of the survey. The remaining 397 women were in their PNC stage and were eligible for follow-up.

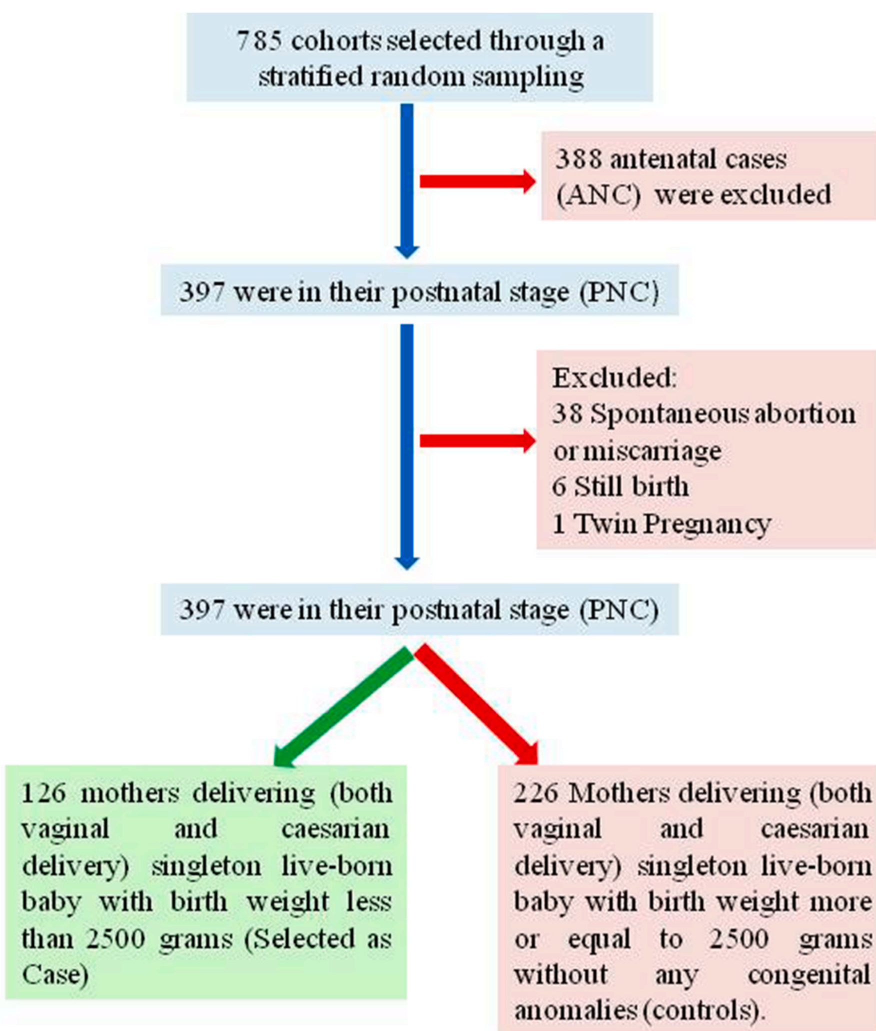

Fig. 1. Flow diagram of the sample design.

However, 45 cases of these PNCs (38 spontaneous abortions or miscarriages, 6 still births and 1 twin pregnancy) were excluded, as these pregnancies did not result in a viable singleton live birth (Supplementary Table 1 and Fig. 1).

This stepwise reduction represented a post hoc sample refinement intrinsic to cohort follow-up studies, rather than a priori sample size determination. This resulted in a final analytical sample of 352 participants. Considering the number of predictors included and the observed outcome frequency, the sample size was considered adequate for the predictive modeling. No post hoc power calculation was performed because retrospective power based on observed effects was conceptually limited; instead, sample adequacy was judged by outcome prevalence, predictor count, model complexity, and internal validation, which showed stable model performance.[18]

The final sample comprised 352 participants and was further classified into two groups:

2.1.1. Case

The case group comprised 126 PNC mothers who had delivered singleton live-born infants (through both vaginal and caesarean delivery) weighing less than 2500 g, without any congenital anomalies, and who were permanent residents of the study area.

Among 126 recorded LBW cases (i.e., <2.5 kg), the median birth weight was 2.2 kg. As very few infants met the World Health Organization (WHO)-defined very low birth weight (VLBW) threshold (<1.5 kg), a study-defined VLBW subgroup (<2.2 kg) was adopted solely for analytical stratification. Thus, the WHO-defined VLBW category was retained conceptually but was not used in the present study for subgroup modeling due to an insufficient sample size.[1,16]

This internal pragmatic classification does not represent the standard WHO definition of VLBW (<1.5 kg) and should not be interpreted as a clinical replacement for the WHO definition, which remains the global reference [16]. Using this study-specific threshold (median birth weight was 2.2 kg), 45.2% of the LBW infants weighed <2.2 kg (study-defined VLBW), indicating a high-risk subgroup within the LBW population.

2.1.1.1. Control. The control group comprised 226 PNC mothers who delivered singleton live-born babies (through both vaginal and caesarian delivery) with a birth weight of 2500 g or more, without any congenital anomalies and who were permanent residents of the study area. This breakdown is presented in detail in Table 1 and illustrated in the revised Fig. 1.

2.2. Data collection and variable construction

Data were collected based on a structured schedule organized into four conceptual domains, which formed the basis for the four ANN models. These conceptual domains are described below-

The socio-demographic and economic domain (Model 1) comprised factors including maternal age, age at marriage, family income, wealth index, education, occupation, family type, availability of in-house toilet facilities, and the practice of open defecation. These variables captured the structural and household-level determinants that shaped long-term exposure to risk and access to resources.

The prenatal conditions and service utilization domain (Model 2) comprised factors including maternal age, gestational age of delivery, time of pregnancy registration, miscarriage, parity, stillbirth, reproductive health awareness, whether ultrasonography (USG) was performed, regular consumption of iron and folic acid (IFA) supplements, age at marriage, insufficient overall prenatal care, gravida, at least four ANC checkups, the practice of open defecation, and more than four ANC visits. This domain reflected the ANC continuum and early pregnancy-related risk states.

The maternal complications and morbidity domain (Model 3) comprised factors including hemoglobin level, gestational age of delivery, miscarriage, stillbirth, excessive vomiting, constipation and gastritis, tuberculosis (TB) in pregnancy, severe abdominal pain, maternal age, gestational vaginal bleeding, measles, eclampsia, urinary tract infection (UTI), adverse pregnancy history, hypertension, gestational diabetes, nausea and vomiting, thyroid disorders, anemia, edema, and jaundice associated with preeclampsia. This group focused on clinical morbidity during pregnancy that could directly affect fetal growth and gestational duration.

The maternal nutritional domain (Model 4) comprised factors including pre-pregnancy body mass index (BMI), maternal age, hemoglobin level, third trimester weight, regularity of food intake, gestational weight gain (GWG), gestational anemia, and deviation of GWG from the recommended standard, which were included in Model 4. The following section details the procedures and instruments used to collect data for certain indicators within these four domains.

The socio-demographic and economic status was assessed using *Wealth Index*, based on the NFHS-5 standard of living index (SLI), which measures household living standards by assessing ownership of 27 items (i.e. house type, toilet facilities, fuel source, and consumer durables), to classify households into low, medium, or high SLI categories.[17] Additionally, the B.G. Prasad scale, adjusted using the All India Consumer Price Index (AICPI), was applied to account for per capita monthly income relative to family size.[19] To accurately reflect the socio-economic conditions in this agriculturally dominant region, an aggregate SLI was derived by combining weighted values from both the NFHS and B.G. Prasad scales, providing a comprehensive measure of wealth and living standards.

Age at marriage data were collected through interview recall methods, and the co-occurrence of puberty and marriage was also assessed.

Gestational weight gain (GWG) and BMI were measured using properly calibrated survey instruments and portable equipments. The first trimester weight record was taken as a proxy measure for pre-pregnancy weight.[20,21] The Institute of Medicine (IOM) published a weight gain guideline for singleton pregnancies based on pre-pregnancy BMI.[21] In the present study, *total gestational weight gain (GWG)* was considered rather than trimester-specific weight gain patterns. Previous analysis have shown a positive association between GWG and increased neonatal birth weight,[21,22] making GWG an important predictor of birth outcomes in the present study.

Maternal weight was recorded in the first trimester (as a proxy for pre-pregnancy weight) and again before delivery or at the end of the third trimester. The difference between these measurements was calculated to obtain the total GWG for each respondent. This approach was consistent with established research practices in maternal health studies, where first trimester weight is commonly considered a valid proxy for pre-pregnancy weight in the absence of direct pre-conception records.[20]

Hemoglobin (Hb) levels were measured using portable hemoglobinometer (HemoCue Hb 201+) through minimally invasive point-of-care capillary blood sampling method, using a single-drop blood sample obtained by finger prick,[23] following WHO-recommended procedures for hemoglobin assessment in populations, while maintaining appropriate standards for maternal health studies.[24] The *Hb* values were further cross verified with available medical reports of the respondents.

To evaluate the *regularity of food intake* among the respondents, the study adopted a widely used one- month retrospective dietary recall method to assess meal frequency and dietary regularity. This cost-effective method, commonly used in developing countries, helps minimize recall bias by focusing on dietary patterns rather than exact quantities.[25]

The collected variables were subsequently classified according to their measurement characteristics and analytical requirements for ANN model development. The continuous independent variables which remain unchanged were – maternal age, age at marriage, pre-pregnancy BMI, actual weight gain, deviation from recommended weight gain, total morbidity score, total nutritional intake score, hemoglobin level. In

Table 1
Demographic characteristics of the LBW and control groups.

Domain ANN Model	Characteristics	No. (%) of participants		*P* value[a]	ANN Relevance
		LBW group (n = 126)	Control Group (n = 226)		
Model 1: Socio-demographic and economic condition (AUC 0.633)	**Age at marriage**				
	<18 Years	97 (77)	142 (62.8)	0.004	**Top Predictor**
	18 or >18 +Years	29 (23)	84 (37.2)		
	Ethnicity				**Moderate Importance**
	General	13 (10.3)	36 (15.9)	0.076	
	OBC-A	40 (31.7)	91 (40.3)		
	OBC-B	3 (2.4)	9 (4)		
	SC	50 (39.7)	63 (27.9)		
	ST	20 (15.9)	27 (11.9)		
	Education				
	Illiterate and Primary	89 (70.6)	109 (48.2)	0.006	**Significant Predictor**
	Junior High	21 (16.7)	43 (19)		
	Secondary	11 (8.7)	55 (24.3)		
	HS	2 (1.6)	14 (6.2)		
	Graduation	3 (2.4)	5 (2.2)		
	Wealth index				
	Poorer	92 (73)	111 (49.1)	0.004	**Significant Predictor**
	Middle	28 (22.2)	67 (29.6)		
	Richer	6 (4.8)	48 (21.2)		
Model 2: Prenatal conditions and services	**Gravida**				
	First Pregnancy	56 (44.4)	106 (46.9)	0.893	
	2	45 (35.7)	78 (34.5)		
	3	16 (12.7)	30 (13.3)		
	4 or >4	9 (7.1)	12 (5.3)		
	Parity				
	First Pregnancy	9 (7.1)	11 (4.9)	0.539	
	1	55 (43.7)	114 (50.4)		
	2	46 (36.5)	67 (29.6)		
	3	12 (9.5)	24 (10.6)		
	4 or >4	4 (3.2)	10 (4.4)		
	Time of pregnancy registration				
	not done	8 (6.3)	12 (5.3)	0.102	
	1st trimester	30 (23.8)	80 (35.4)		
	2nd trimester	77 (61.1)	123 (54.4)		**Late ANC key risk**
	3rd trimester	11 (8.7)	11 (4.9)		
	USG done				
	No	70 (55.6)	97 (42.9)	0.015	High Importance
	Yes	56 (44.4)	129 (57.1)		
	Consumed IFA				
	No	54 (42.9)	75 (33.2)	0.046	
	Yes	72 (57.1)	151 (66.8)		
	Utilization of ANC				
	<4 visit	74 (58.7)	101 (44.7)	0.008	High Importance
	4 and > 4 visit	52 (41.3)	125 (55.3)		
	Overall insufficient ANC				
	No	78 (61.9)	169 (74.8)	0.008	High Importance
	Yes	48 (38.1)	57 (25.2)		
	Type of delivery				
	Vaginal	121 (96)	203 (89.8)	0.028	
	Caesarean	5 (4)	23 (10.2)		
	Place of delivery				
	Institutional delivery	91 (72.2)	203 (89.8)	0.006	
	Non-institutional or Home delivery	35 (27.8)	23 (10.2)		**Significant Predictor**
Model 3: Maternal complications, delivery and morbidity factors	**Gestational age of delivery**				
	Premature	13 (10.3)	5 (2.2)	0.001	**Significant Predictor**
	Full Term	113 (89.7)	221 (97.8)		
	Adverse pregnancy history				**Moderate Importance**
	No	105 (83.3)	206 (91.2)	0.023	
	Yes	21 (16.7)	20 (8.8)		
	Age at pregnancy				
	<15	7 (5.6)	4 (1.8)	0.056	
	15-18	33 (26.2)	44 (19.5)		
	19-25	71 (56.3)	131 (58)		
	26-35	12 (9.5)	40 (17.7)		

(*continued on next page*)

Table 1 (*continued*)

Domain ANN Model	Characteristics	No. (%) of participants		*P* value[a]	ANN Relevance
		LBW group (n = 126)	Control Group (n = 226)		
	36-44	3 (2.4)	7 (3.1)		
	Pre-pregnancy BMI				**Moderate Importance**
	Underweight	60 (47.6)	104 (46)	0.042	
	Healthy weight	49 (38.9)	98 (43.4)		
	Overweight	14 (11.1)	14 (6.2)		
	Obesity	3 (2.4)	10 (4.4)		

[a] The difference in distribution of each variable between the LBW and control groups was tested with the Pearson χ2 test.

contrast, some continuous independent variables that were converted to categorical variables to decrease the effect of extreme values and outliers. These included the standard of living score, neonatal birth weight, gravida and parity.

2.3. Statistical analysis

Bivariate associations between independent variables and LBW were tested through binary logistic regression (BLR). The logistic regression model estimated the probability (p) of LBW using the equation:

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \quad (1)$$

Where,

The model was found to be significant based on the Omnibus test of model coefficients ($p < 0.05$). The Hosmer-Lemeshow test was used to assess the goodness-of-fit of the regression model and indicated an adequate fit ($\chi^2 = 0.383$, $p = 0.383 > 0.05$).[26] The classification table indicated that the model correctly predicted 73% of the cases after inclusion of the predictors in the model (Supplementary Table 2).

2.3.1. ANN model construction

The ANN predictive modeling was chosen due to its non-parametric, assumption-free nature. The ANN models were developed using SPSS v22 (®IBM Inc.Armonk, NY, USA). No additional packages were required. Data processing including normalization, train-test splitting, and binary logistic regression was performed within SPSS v22.

The model structure comprised three layers. The input layer consisted of the selected predictors, while the output layer had two neurons representing study-defined VLBW and LBW classes. The optimal number

Table 2
Putative predictive factors for predicting low birth weight.

Characteristics	B	*P* value	OR (95% Cl)
Age at pregnancy[a]		0.193	
15-18	0.435	0.560	1.544 (0.358-6.658)
19-25	0.666	0.356	1.947 (0.473-8.015)
26-35	1.309	0.101	3.701 (0.774-17.705)
36-44	1.830	0.087	6.233 (0.768-50.569)
Education[b]		0.121	
Junior High	0.344	0.318	1.411 (0.718-2.773)
Secondary	1.014	0.014	2.758 (1.223-6.218)
HS	0.419	0.620	1.521 (0.290-7.966)
Graduation	−0.583	0.482	0.558 (0.110-2.832)
Wealth index[c]		0.038	
Middle	0.362	0.227	1.436 (0.799-2.582)
Richer	1.261	0.016	3.531 (1.268-9.834)
USG done or not (yes)[d]	−0.114	0.682	0.892 (0.517-1.540)
Whether consumed IFA regularity (yes)[e]	0.217	0.433	1.242 (0.722-2.136)
Kotelchuck ANC utilization index (4 or >4 visit)[f]	0.192	0.503	1.212 (0.690-2.129)
Gestational age of delivery (full-term)[g]	2.236	0.001	9.352 (2.370-36.898)
Place of delivery (non-institutional/home)[h]	−0.684	0.059	0.505 (0.248-1.027)
Type of delivery (c-section)[i]	0.867	0.148	2.379 (0.736-7.693)
Total morbidity score	−0.003	0.905	0.997 (0.941-1.055)
Regularity in food intake	0.101	0.003	1.106 (1.036-1.181)
Pre-pregnancy BMI	−0.050	0.112	0.951 (0.895-1.012)
Adverse pregnancy history (yes)[j]	0.045	0.016	1.046 (1.008–1.086)
Insufficient overall prenatal care	−0.270	0.375	0.763 (0.420-1.386)
Age at marriage	0.385	0.212	1.470 (0.803-2.692)
Pregnancy complication	−0.021	0.638	0.979 (0.895-1.070)
Constant	−3.419	0.011	0.033

[a] Reference to age at pregnancy of 15 years or younger.
[b] Reference to education of illiterate or primary.
[c] Reference to wealth index poorer.
[d] Reference to USG to not done.
[e] Reference to IFA regular consumption to no.
[f] Reference to kotelchuck ANC utilization to <4 visit.
[g] Reference to Gestational age of delivery to preterm.
[h] Reference to place of delivery to institutional.
[i] Reference to type of delivery to vaginal.
[j] Reference to adverse pregnancy history to no.

Table 3
Comparison of the performance of 4 artificial neural network models.

Model	AUC	Sum of Square Error (Training)	Sum of Square Error (Testing)	RMSE (Training)	RMSE (Testing)	Accuracy (Training %)	Study-defined VLBW		LBW	
							Sensitivity	Specificity	Sensitivity	Specificity
Model 1[a]	0.633	20.115	10.103	0.489	0.490	60.700	0.600	0.620	0.670	0.560
Model 2[b]	0.716	20.109	6.330	0.463	0.445	66.000	0.810	0.580	0.590	0.790
Model 3[c]	0.756	19.868	4.028	0.446	0.394	67.000	0.840	0.550	0.740	0.660
Model 4[d]	0.699	19.077	8.611	0.468	0.470	64.100	0.550	0.820	0.870	0.510
Mean	0.701	19.792	7.268	0.466	0.450	64.450	0.700	0.643	0.718	0.630
Std Dev	0.051	0.491	2.659	0.018	0.042	2.774	0.146	0.122	0.119	0.124

Abbreviations.
AUC = area under the curve, RMSE = root mean squared errors.
[a] Model 1 included significant socio-demographic and economic conditional factors (i.e. maternal age, age at marriage, family income, wealth index, education, occupation, family type, availability of in house toilet facility, practicing open defecation).
[b] Model 2 included significant the prenatal conditions and factors of utilization of services (i.e. maternal age, gestational age of delivery, time of pregnancy registration, miscarriage, parity, still birth, reproductive health awareness, USG done or not, regular consumption of IFA, age at marriage, insufficient overall prenatal care, gravida, at least ANC check ups, practicing open defecation, >4 ANC check ups).
[c] Model 3 included significant maternal complications and morbidity factors (i.e. hemoglobin level, gestational age of delivery, miscarriage, still birth, excessive vomiting, constipation and gastritis, TB in pregnancy, severe abdominal pain, maternal age, gestational vaginal bleeding, measles, eclampsia, UTI, adverse pregnancy history, hypertension, gestational diabetes, nausea and vomiting, thyroid, anemia, edema, jaundice with preeclampsia).
[d] Model 4 included significant factors of maternal nutritional condition (i.e. pre-pregnancy BMI, maternal age, hemoglobin level, third trimester weight, regularity of food intake, GWG, gestational anemia, deviation of GWG from standard).

of neurons was determined to be four per hidden layer. Hence, the optimal network topology was N-i-4-4-2 (i input predictors → 4 neurons per hidden layer × 2 → 2 output neurons representing the study-defined VLBW/LBW classes) [9,11,27–29].

The sigmoid activation function transforms ANN outputs into probabilities (0–1), enabling intuitive interpretation of LBW risk identification and facilitating clinical decision-making [27–29]. A feed-forward ANN model framework was applied to construct the predictive models. The approximate solution $yN(x)$ of the feed forward neural network, based on the network parameter Ω, was represented by the following equations (2)–(5), which were adopted from previous studies [9,11,26–28].

$$yN(x) = y_o + (x - x_o)\, N\,(k, \Omega) \tag{2}$$

Where, the output $N\,(k, \Omega)$ was given below, using input as x and a vector containing corresponding weights of Ω.

$$N\,(k, \Omega) = \sum_{i=1}^{k} v_i \phi(z_i),\ z_i = w_i x + u_i \tag{3}$$

$$N(x) = N\,(k, \Omega) = \sum_{i=1}^{k} v_i \frac{1}{1 + e^{-z_i}} = \sum_{i=1}^{k} \frac{v_i}{1 + e^{-(w_i x + u_i\,)}} \tag{4}$$

w_i denoted weight between the input and i^{th} hidden unit; v_i denoted the weight between i^{th} hidden unit and the output unit, u_i denoted the bias to i^{th} hidden node, and the sigmoid function ϕ (.) is given as[11,29] -

$$\phi\,(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Where, ϕ (.) function is referred to as activation function.

Hyperparameters were optimized through an iterative trial-and-error process, where different configurations, including the number of hidden layers (fixed at 2), number of neurons per layer (4), and learning rate (0.01 - 0.30), were repeatedly adjusted and tested by training the model for multiple iterations (up to 100 epochs), with each iteration evaluated based on its performance on the training dataset. This process continued until a configuration yielding the best comparative performance was identified.[11,28,29]

2.3.2. ANN model evaluation

Model performance was evaluated using five repeated 70/30 train-test splits to indentify the model with the lowest prediction error and minimum overfitting.[2,6,10] To reduce overfitting, the model architecture was kept simple (N-4-4-2), with a fixed number of 100 epochs, corresponding to the maximum number of iterations.[6,9,10] The model performance was further validated using an independent test set (30% or n ≈ 106 cases), while cross-validation was performed to assess the internal consistency of the results.

ANN operation began with the normalization (equation (6)) of input data, whereby the inputs and targets were scaled within the range of [−1,1], corresponding to the minimum and maximum values, respectively.[27]

$$y = \frac{(y_{max} - y_{min})*(x - x_{min})}{(X_{max} - X_{min})} + y_{min} \tag{6}$$

where, 'y' was the normalized value of X, 'y_{max}' was 1, 'y_{min}' is −1, 'X' was the actual value of parameter of interest (independent variable), 'X_{min}' was the minimum value of the parameter of interest, 'X_{max}' was the maximum value of the parameter of interest.[27]

Normalized predictor importance (scaled from 0 to 100%) was assessed using partial derivatives or connection-weight-based sensitivity analysis methods, applied to the trained ANN, following Gevrey et al.[9] This approach allowed the identification of the top predictors (e.g., hemoglobin level at 99.5% importance in Model 3).[9,10]

The study evaluated the area under the receiver operating characteristic curve (ROC) $[P(F_p) = \alpha, P(T_p) = 1 - \beta]$, accuracy, sensitivity, specificity, and the percentages of correctly and incorrectly classified cases.[27,30,31] The ROC plot provided a graphical representation of the discriminatory accuracy visualization of binary classification models and the area under the curve (AUC) served as a common measure of of discriminatory performance, as represented by equation 6.[28,30,31]

$$AUC = \sum_i \left\{ (1 - \beta_i.\Delta\alpha) + \frac{1}{2}[\Delta(1 - \beta).\Delta\alpha] \right\} \tag{7}$$

Where,

$$\Delta(1 - \beta) = (1 - \beta_i) - (1 - \beta_{i-1}), \tag{7.1}$$

$$\Delta\alpha = \alpha_i - \alpha_{i-1} \tag{7.2}$$

The root mean squared errors (RMSE) of each model were calculated as a measure of prediction errror (equation (8)). Lower the value of RMSE, smaller is the prediction error of the model. It tends to decrease with larger datasets.[29,31]

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{p,i} - X_{\alpha,i}\right)^2} \tag{8}$$

2.3.3. F1 score calculation for each model

F1 Score for each model was calculated to provide balanced measure by considering both precision (the proportion of correctly predicted positives) and recall (the proportion of actual positives correctly identified).[30] This measure is particularly useful for imbalanced datasets where accuracy alone can be misleading.[31] Precision provides a direct and intuitive measure of prediction correctness.[31]

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

Where, Precision = True Positives (TP)/[True Positives (TP) + False Positives (FP)]; Recall = Sensitivity = True Positives (TP)/[True Positives (TP) + False Negatives (FN)].[30,31]

This evaluation framework was based on internal validation using repeated random train–test splits of the same dataset. Therefore, the reported performance reflected internal consistency and did not establish external generalizability. Accordingly, the findings should be interpreted as exploratory model development results rather than as definitive predictive tools for clinical deployment.

3. Result

3.1. Participants characteristics

Out of 352 rural women (mean age 21.87 ± 5.01 years), 35.8% delivered LBW infants (<2.5 kg). The highest proportion of study-defined VLBW (birth weight <2.2 kg, corresponding to the study median) was observed among women aged 15-18 years and >18-25 years (28.1% and 49.1% respectively), with the majority of cases occurring among women with BMI <18.5 kg/m^2 (56.1%). Child marriage (<18 yrs) was significantly higher among LBW mothers (77% vs 63% in the control group). The results align with global evidence, where approximately 21% of women were married before the age of 18years, with South Asia contributing the largest burden.[32] Higher proportions of LBW cases were observed among poor illiterate mothers (73%).[32] Additional significant risk factors included late registration of pregnancy (second trimester, 61.1%), past adverse pregnancy history (83.3%) and underutilization of services, such asno USG (55.6%), inadequate or no consumption of IFA (42.9%), and underutilization of prenatal care services (58.7%). This descriptive pattern directly shaped the ANN model construction by confirming domain-specific risk gradients (Table 1).

3.2. Putative predictive factors

The risk of having LBW offspring was 6.233 (95% CI, 0.768-50.569; $P = 0.087$) times higher among women who had pregnancy between the ages of 36-44 yrs, and 1.046 (95% CI, 1.008–1.086; $P < 0.016$) times higher among those who had an adverse pregnancy history. While, the chances of LBW were 0.108 times lesser if adequate USG was undertaken. Regularity in food intake (OR, 1.106; 95% CI, 1.036-1.181; P = 0.003), gestational age of delivery (OR, 9.352; 95% CI, 2.370-36.898; P = 0.001), adverse pregnancy history (OR, 1.046; 95% CI, 1.008–1.086; P = 0.016) were identified as risk factors for having LBW offspring (Table 2).

3.3. ANN predictive models

3.3.1. Performance assessment

Among the four models, Model 3 exhibited the highest AUC of 0.756, followed by Model 2 (AUC of 0.716) and Model 4 (AUC of 0.699), while Model 1 showed weakest discriminatory performance (AUCof 0.633). For each model, the AUC values were identical for both the study-defined VLBW and LBW categories, indicating equal discriminatory performance rather than identical shapes of ROC curve. According to the criteria of the University of Utah, Department of Mathematics, Model 3 and Model 2 (AUC of 0.716) demonstrated fair discriminatory ability.[29,33,34] However, the observed AUC range (0.63-0.75) indicated moderate rather than strong predictive performance (Table 3, Fig. 2). These findings suggested that, although the models were able to distinguish between LBW and non-LBW cases, their predictive utility was expected to be more reliable within population resembling the characteristics of the study cohort, as these models were internally evaluated through repeated split-sample procedures, highlighting the need for external validation to confirm broader generalizability.

Consistent with the above findings, the Root Mean Squared Error (RMSE) analysis further highlighted the predictive performance of the models. Model 1 and Model 4 showed higher RMSE, lower AUC and poorer classification accuracy, indicating suboptimal model fit. In contrast, Model 3 (RMSE = 0.394) and Model 2 (RMSE = 0.463), demonstrated comparatively better model fit and predictive stability. Although RMSE values < 0.5 are generally considered acceptable for prediction tasks, this should be interpreted cautiously as a measure of internal consistency rather than external predictive validity.[29,34]

With respect to sensitivity, Model 4 achieved the highest LBW sensitivity (0.870), outperforming Model 3 (0.740) and Model 2 (0.590). Meanwhile, Model 3 showed a slightly higher study-defined VLBW sensitivity (0.840) than Model 2 (0.810) and demonstrated a more balanced overall performance. Therefore, Model 4 was most effective for detecting true LBW cases due to its higher sensitivity, while Model 3 offered greater overall versatility across multiple evaluation metrics. However, these findings reflected performance trade-offs within the same dataset and should not be interpreted as definitive clinical superiority of any single model.

3.3.2. The variable importance plot and calibration plot

The *Variable Importance Plot* of Model 1 emphasized maternal age and socioeconomic conditions as the primary determinants of LBW. In Model 2, maternal age, gestational timing, reproductive history, and prenatal care factors emerged as key contributors. Model 3 (Fig. 3) identified hemoglobin level (99.5% importance), gestational age (63.6%), past pregnancy history and maternal morbidity as the top predictors, whereas Model 4 identified pre-pregnancy BMI as the principal predictor of LBW.

The results of the calibration analysis showed a clear variation in model performance. Model 1 performed very poorly with negligible agreement between observed and predicted values ($R^2 = 0.0042$). In contrast, Model 2 showed a good level of calibration ($R^2 = 0.6788$), indicating reasonable predictive ability. Models 3 and 4 demonstrated excellent calibration with very high agreement ($R^2 \approx 0.93$–0.94) and minimal prediction bias. Among these, Model 4 performed slightly better, however, both models exhibited high calibration reliability for prediction (Fig. 4).

3.3.3. F1 score and goodness of model fit

The *F1* scores varied across the four ANN models, reflecting differences in classification consistency and overall predictive balance. Model 2 showed the highest F1 scores for both study-defined VLBW (0.677) and LBW (0.675), followed by Model 3 (0.662 and 0.698), indicating relatively strong and consistent classification performance. While Model 4 showed moderate F1 scores, whereas Model 1 exhibited the lowest performance (Table 4). Overall, Model 3 emerged as the most reliable

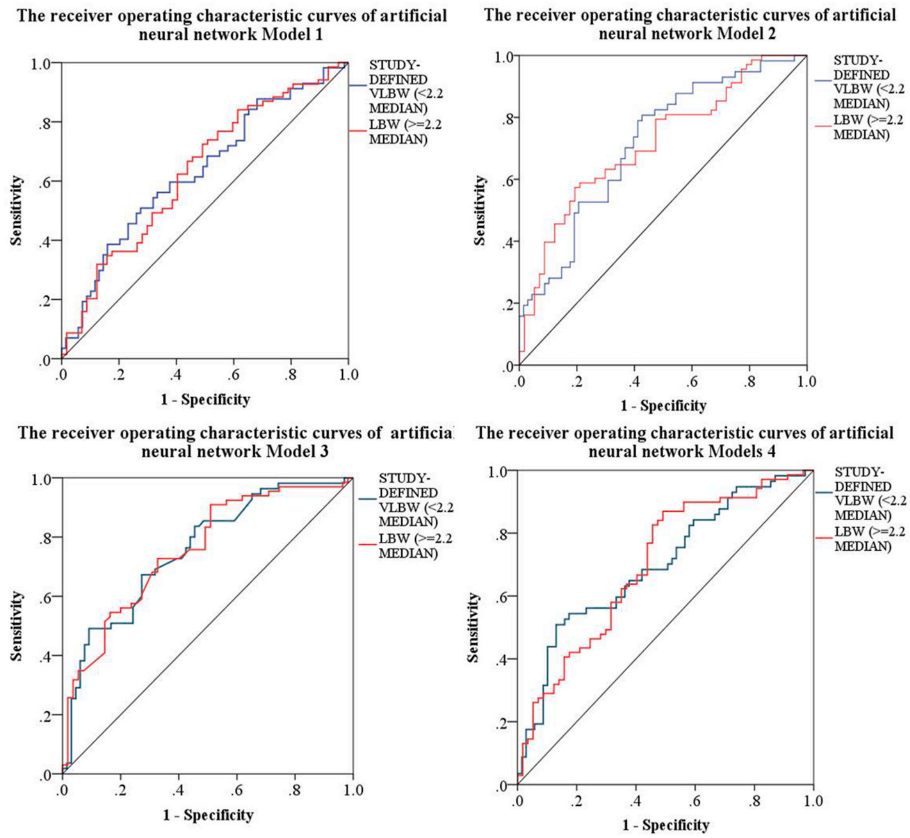

Fig. 2. The Receiver Operating Characteristic (ROC) Curves of 4 Artificial Neural Network Models
[Area under curve (AUC) of Model 1: 0.633, Model 2: 0.716, Model 3: 0.756 and Model 4: 0.699].

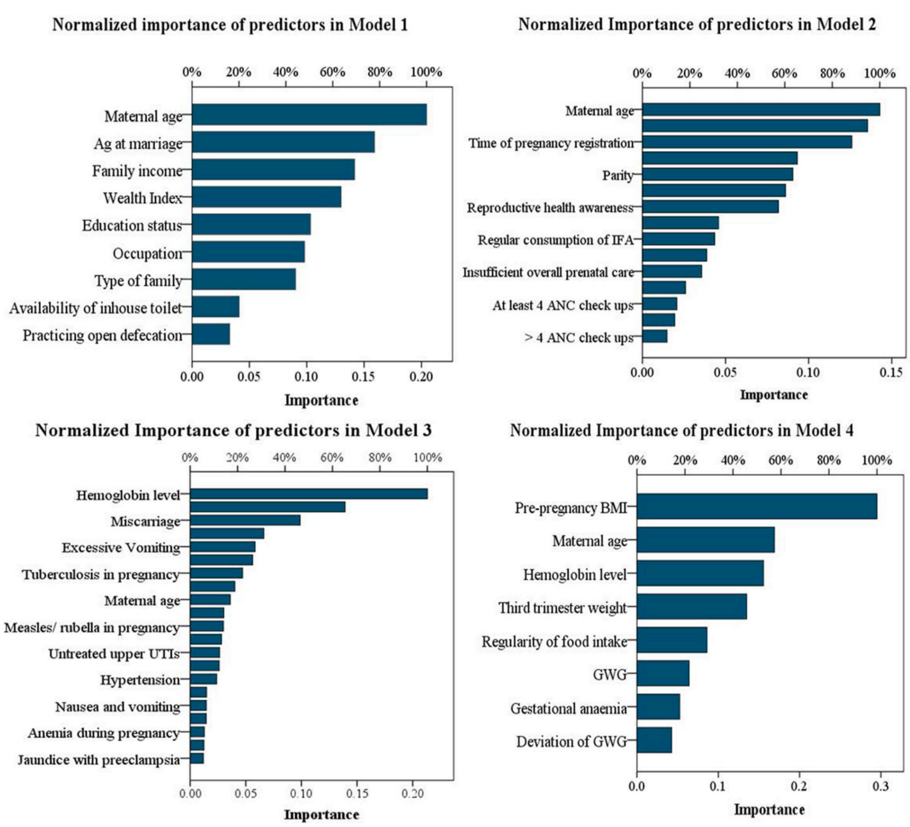

Fig. 3. Variable Importance for all four models for Predicting the Risk of Low Birth Weight in Neonates.

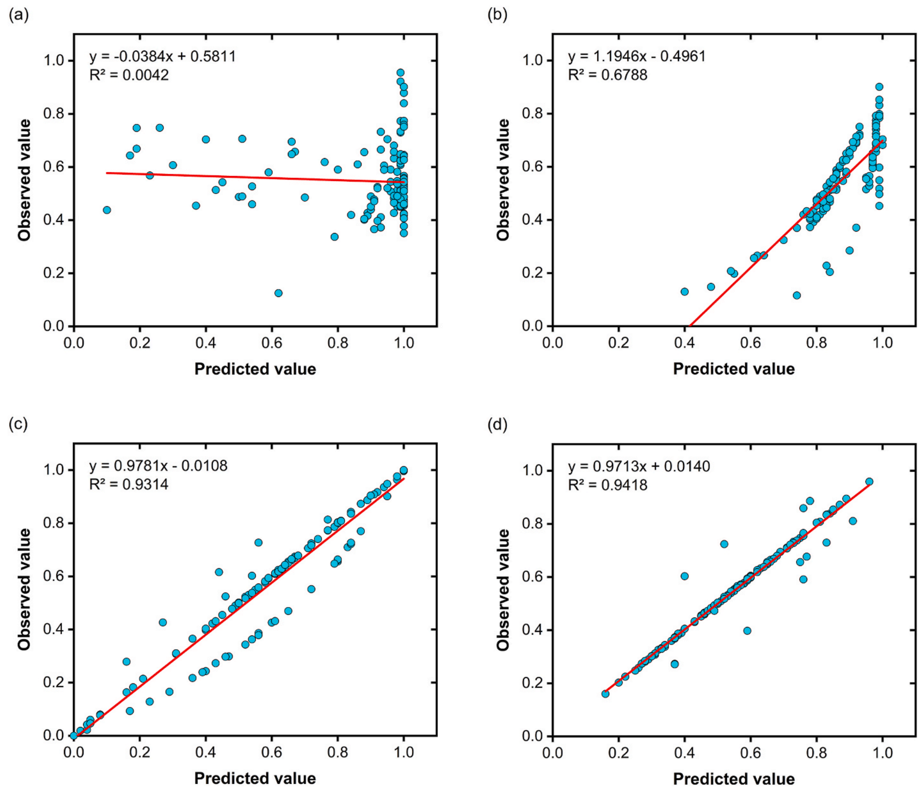

Fig. 4. The calibration plot of (a) Model 1 (Included significant socio-demographic and economic conditional factors), (b) Model 2 (Included significant the prenatal conditions and factors of utilization of services), (c) Model 3 (Included significant maternal complications and morbidity factors) and (d) Model 4 (Included significant factors of maternal nutritional environment).

Table 4
F1 Score of each model and Over fitting and Under fitting Analysis.

Model	F1 Score (Study-defined VLBW)	F1 Score (LBW)	Overfitting/Underfitting Comments
Model 1	0.610	0.610	Training and testing RMSE almost equal, SSE testing lower → No overfitting, model fits well
Model 2	0.677	0.675	Testing RMSE lower than training, SSE much lower in testing → No overfitting, possible underfitting
Model 3	0.662	0.698	Testing error lower than training → Likely no overfitting, Good generalization
Model 4	0.655	0.642	Training and testing errors similar, SSE testing lower → No overfitting, balanced fit

and well-balanced model for this dataset, demonstrating good predictive performance and consistent performance during internal validation (Table 4).

To address sample adequacy and model reliability, this sample size (n = 352 out of 785, with a split of 70% for the training set ≈246 cases and a 30% for the testing set ≈106 cases) was considered adequate for ANN modeling. This was supported by: (1) stable performance across five repeated splits, (2) low test RMSE (0.394, Model 3) without evidence of overfitting, and (3) moderate AUC (Model 3, 0.756), indicating reasonable predictive performance in this setting. Collectively, these findings confirmed a reasonable basis for small-sample exploratory ANN modelling in rural maternal health prediction [6,35–39].

4. Discussion

Studies have employed a wide range of statistical and machine learning techniques to predict the risk of LBW, including logistic regression [35–37,40], tree-based machine-learning models, such as decision tree classification and random forest classification[35–39,41], deep learning feed forward, support vector machines (SVMs), permutation feature classification with k-nearest neighbors,[35,37,41,42] as well as hierarchical structure analysis, spatial autocorrelation,[43] minimum error rate classifier models,[44] ANN model[35,45,46] etc. Despite these advances, relatively few studies have developed comprehensive predictive frameworks integrating multiple putative risk domains for effective LBW risk assessment and stratification. This limitation has restricted the ability to generate actionable, region-specific insights for targeted interventions, particularly in high-burden settings such as rural India.

Conventional approaches, including logistic regression, random forest, and gradient boosting, remain widely applied, however, they may be less effective in capturing complex nonlinear relationships due to their underlying structural assumptions [35–37,40]. Logistic regression relies on the assumption of linear associations, whereas tree-based approaches may inadequately represent complex nonlinear interactions among predictors. In contrast, ANNs provide a flexible, assumption-free framework that enables more effective pattern recognition in complex, high-dimensional maternal health data.[45,46] Nevertheless, the comparative performance of ANN models observed in this study was confined to internal validation and warrants further evaluation through external validation in independent populations to establish evidence of superior clinical performance.

Within this analytical framework, maternal hemoglobin level and gestational age of delivery emerged as significant predictors of LBW neonates. Previous studies have also identified lower maternal hemoglobin levels as one of the strongest risk factors for LBW, as maternal anemia may impair placental angiogenesis, reducing oxygen supply to fetus, restricting intrauterine growth and ultimately resulting in LBW [47–50]. PTB and LBW are associated with long-term adverse outcomes, especially in early preterm infants born at <32 weeks of gestation.[51,52]

The present study identified an adverse pregnancy history as a key predictor of LBW, consistent with earlier evidence, suggesting that stillbirth and spontaneous abortion increase the risk of adverse maternal outcomes and LBW.[53,54] Several studies have reported that recurrent pregnancy loss (RPL) increases the risk of PTB, premature rupture of membranes (PROM), and LBW by disrupting endometrial receptivity and vascular remodeling, thereby increasing susceptibility to such adverse outcomes in subsequent pregnancies.[54]

Previous studies have confirmed that the presence of chronic diseases and morbidity factors (Model 3) is associated with higher risk of LBW neonates,[54,55] including conditions such as-excessive vomiting or hyperemesis gravidarum (HG).[56–58] Additional factors, including maternal age and socio-economic background, also contribute significantly to the risk of LBW.[52] Previous studies have shown that the increased risk of LBW and PT observed among teenage mothers is largely explained by socio-economic factors, with the excess risk diminishing after adjusting for these factors. However, an elevated risk persists among very young (<16 years) and older (>35 years) mothers.[59–61]

The findings of the present study are also aligned with previous studies confirming that a low pre-pregnancy BMI ($<18.5\,kg/m^2$) is associated with an increased risk of LBW infants compared to those born to obese mothers.[62] Maternal nutritional status and dietary intake during pregnancy may also influence neonatal birth weight, further supporting the findings of Model 4 in the present study.[63,64] A significant risk of LBW was observed among young rural Indian pregnant women with poor nutritional status.[64]

The study emphasized that inadequate utilization of ANC services increased the risk of LBW, which is consistent with previous studies [65–68]. Studies have also reported that having only one ANC visit or fewer than four ANC consultations is associated with a higher risk of LBW[69,70]. The findings also indicated that poor sanitation and the practice of open defecation increased the risk of adverse pregnancy outcomes, including PTB and LBW, aligning with the observations of previous studies.[71–73] Additionally, the study found that multiparous mothers were more likely to have LBW infants than primiparous mothers, which is supported by earlier evidence.[44,74]

5. Strengths and limitations

(i) The first strength of the study is its contribution to addressing the gap in identifying the risk of LBW at an early stage using four ANN models. Given the data availability, the study incorporated four sets of putative predictive factors (i.e., socio-demographic, prenatal, morbidity, and nutritional factors) that a mother is likely to experience. (ii) The study developed an ANN-based predictive framework that may serve as a rapid and effective tool for early prediction of LBW risk, enabling targeted intervention to reduce the risk at the earliest stage of pregnancy, such as micronutrient supplementation and improved maternal care and oral supplementation[75,76]. (iii) Lastly, the model was purposefully developed to capture region-specific characteristics rather than to provide broad generalizations. The use of ANN enabled the model to hand multi-factorial, non-linear datasets.

However, a key limitation of the study is the use of self-reported data, which may be subject to recall bias and social desirability bias; for example, there might be ambiguity in reporting respondents' age at marriage because age registration is largely unpracticed in the study area. Additionally, cases without proper supporting medical documentation for any disease were excluded from the study.

Furthermore, the study underwent repeated train–test splits to evaluate model stability, although the dataset used was derived from the same study population. Therefore, the predictive capacity of the models should be interpreted within the context of similar study populations and the internal validation framework, and their applicability to independent datasets with different sociodemographic and superior clinical settings needs to be established through external validation.

6. Conclusions

This predictive analysis identified Model 3 (maternal complications and morbidity factors), as the best performing model for classifying LBW severity, followed by Model 2 (prenatal factors and utilization of services). The most influential factors across models included maternal age, gestational age at delivery, hemoglobin levels, adverse pregnancy history, nutritional regularity, and pre-pregnancy BMI. These findings highlight the potential importance of early detection of maternal complications and timely interventions, including adequate maternal nutrition and improved maternal care, which may substantially reduce the risk of LBW. As the analysis was restricted to singleton infants with low birth weight, the proposed framework should be interpreted as a model for classifying LBW severity (VLBW versus LBW) rather than as a model for predicting the occurrence of LBW in the general population.

This ANN-based predictive approach may provide a useful analytical framework for supporting healthcare planning and identifying high-risk maternal and neonatal profiles in resource-constrained rural settings. As these models were internally evaluated, their applicability to boarder population for generalization and further targeted intervention may require further external validation in independent and diverse populations. The findings have nevertheless directed attention towards eliminating underage marriage, promoting maternal education, ensuring nutritional security, and strengthening primary healthcare delivery to improve neonatal outcomes.

Future research may include longitudinal and rural-urban comparative studies along with ethnographic and biological investigations, to reveal structural disparities in implementation of region-specific strategies. Further, these studies should also aim to explore sociocultural, gender and epigenetic determinants of LBW as well as the role of family awareness, paternal involvement, health perception and education, in order to develop a holistic understanding of the determinants of LBW in rural India.

Consent to participate

Data were collected at a single point in time from postnatal mothers (PNC stage), based on their most recent delivery outcomes that satisfied the inclusion criteria. Prior to initiating the research, necessary permissions were obtained from the relevant administrative and health authorities to ensure ethical compliance. These official approvals allowed the authors to conduct field-based data collection in accordance with institutional and governmental ethical standards.

Ethical statement

The authors have taken prior permission from the Director of Health Services, Govt. of West Bengal, Department Health and Family Welfare, with Chief Medical Officer of Health and District Magistrate of the concern study area to carry out the research in this field. Scanned copies of the permission letters are attached herewith.

Ethics approval and consent to participate

The authors have obtained prior permission from the Director of Health Services, Govt. of West Bengal, Department Health and Family Welfare, Sasthya Bhawan, the supreme authority of health-related issues in West Bengal along with Chief Medical Officer of Health and District Magistrate of the concern study area to carry out the research in this field.

Consent for publication

Not Applicable.

Ethical approval of correspondents

The authors have taken prior permission from the Director of Health Services, Govt. of West Bengal, Department Health and Family Welfare, Sasthya Bhawan, the supreme authority of health related issues in West Bengal along with Chief Medical Officer of Health and District Magistrate of the concern district (Birbhum) to carry out the research in this field. We are attaching the scan copies of the permission letters herewith.

Enclosures:

1. Copy of Ethical approval from the Director of Health Services, Govt. of West Bengal, Department Health and Family Welfare, Sasthya Bhawan.
2. Copy of Ethical approval from the District Magistrate of the concern district (Birbhum).
3. Copy of Ethical approval from the Chief Medical Officer of Health (Birbhum).

CRediT author statement

Dr. Alokananda Ghosh (First and Corresponding Author): Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - Original Draft, Visualization.

Dr. Baidyanath Pal (Second Author), Validation, Resources, Review & Editing, Supervision.

Funding info

No specific funding was received for this study.

Competing interests

The manuscript has no conflict of interest.

Acknowledgements

The authors would like to express their sincere gratitude to the Director of Health Services and the Secretary, Department of Health & Family Welfare, Govt. of West Bengal for granting permission to conduct the empirical study. The first author is especially grateful to the Chief Medical Officer of Health (CMOH) and all the Block Medical Officer of Health (BMOH) for their support and assistance throughout the study, particularly in facilitating the ground-level fieldwork and data collection conducted by the first author.The first author also expresses sincere gratitude to Goutam Ghosh, District Statistical Manager, National Health Mission, Dept. of Health & Family Welfare, Govt. of West Bengal, for his valuable assistance and support. The first author is thankful to Dr. Shraban Sarkar, Department of Geography, Cooch Behar Panchanan Barma University, Cooch Behar, West Bengal, India, for his valuable and constructive comments and inputs during the drafting the manuscript, as well as his continuous and sincere support throughout the research process.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cegh.2026.102451.

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