Smart Fetal Growth Monitoring, Real -Time Weight Prediction in High-Risk Pregnancies.

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Abstract— The newborn's low birth weight is one of the most important issues in prenatal care since it can negatively impact the infant's health and, in more severe cases, even result in its death. It is also because of this reason that infant mortality rates show higher numbers all around the globe. Methods of artificial intelligence, especially those based on machine learning (ML), can predict health problems that may occur at birth as well as for the whole duration of gestation. Therefore, our study proposes to study some machine learning (ML) techniques which could be employed to predict if a fetus would be born weighing less than what is expected for its gestational age. The importance of identifying fetal development problems early on is emphasized by the possibility of extending gestation days through timely intervention. Using such an intervention, a decrease in infant morbidity and death would result from the potential to raise fetal weight at birth. Therefore, in this research, we will forecast the fetal birth weight at an early stage and classify them as low weight if their weight is less than 2.5 kg, normal weight if their weight is more than 2.5 kg but less than 4.5 kg, and abnormal weight if their weight is more than 4.5 kg. We will use machine learning techniques and algorithms to estimate the fetal birth weight; in this case, the algorithm will be chosen based on the accuracy achieved by them in the studies we have conducted. Finally, we chose the Random Forest and Linear Regression.

Keywords: random forest, linear regression, neonatal morbidity, gestational age, and infant death rates.

INTRODUCTION

Intrauterine growth restriction (IUGR) and low birth weight (LBW) are major issues in prenatal care that significantly influence the health of the newborn. Low oxygen levels, poor Apgar scores, respiratory issues from meconium aspiration, and hypoglycemia are Some of the effects that may occur due to IUGR, in which the fetus is smaller than others of the same gestational age. In extreme situations, IUGR may cause long-term growth issues or even fetal death. The most severe prenatal development problems are known to be caused by persistent arterial hypertension, and maternal hypertension is the primary cause of IUGR. Increased chances of newborn death, stunted growth, mental retardation, learning disabilities, and chronic illnesses like obesity, diabetes, and heart disease have all been associated with low birth weight. Similarly, challenges including cesarean delivery, extended labor, hemorrhage, and trauma during delivery, as well as the risk of infant hypoxia and death, are linked to large birth weight (macrosomia).

In this context, with the aid of ML, approaches such as Linear Regression and Random Forest Regressor predict and analyze fetal birth weights in order to provide valuable information that can be used by healthcare professionals to make defensible decisions. Machine learning (ML) can help predict low birth weight and identify issues early by seeing trends in huge datasets. This enables prompt interventions and individualized treatment plans. Predicting the fetal birth weight early in pregnancy and categorizing it into three groups—low birth weight (less than 2.5 kg), normal birth weight (2.5–4.5 kg), and abnormal birth weight (more than 4.5 kg)—is the goal of this effort. Reducing maternal and neonatal morbidity and death requires early diagnosis of these disorders.

I. RELATED WORKS

A. *Paper Title: Prediction of Weight Range of Neonate Using Machine Learning Approach, Authors: Aleem Adeeba, Banujan Kuhaneswaran, and B.T.G.S. Kumara, Year of publication: 2022*

Description: Using data from 500 Sri Lankan women, this study predicts newborn birth weight classes using machine learning. Five algorithms are used here: Naive Bayes, ANN, SVM, Logistic Regression, and Decision Trees, which will be useful in finding low-cost solutions for newborn health prediction in low-resource settings.

Methodology: Researchers identified 16 factors affecting neonatal birth weight. Python preprocessed data from 500 prenatal records in Sri Lanka, splitting it into 80% training and 20% testing. Accuracy, recall, precision and F1 scores were evaluated for five models: Naive Bayes, ANN, SVM, Logistic Regression, and Decision Trees. ANN used the Adam optimizer and binary cross-entropy loss.

Limitations: Generalizability and comprehension of neonatal health outcomes may be impacted by the study's limitations, which include its small dataset (500 samples), regional focus on Sri Lanka, and the simple classification of infant weights (<3,200 g and ≥3,200 g).

Key Insights: The study showed how machine learning models can be applied to predict neonatal birth weight, focusing on low-resource settings. Data preprocessing and model evaluation with metrics like accuracy and F1 scores highlighted the effectiveness of these models. However, the small dataset, regional focus, and simplified classification limited generalizability.

B. *Paper Title: Machine learning-based approach for predicting low birth weight, Authors: Ranjbar, A., Montazeri, F., Mehrnoush, V., Farashah, M. V., Darsareh, F., & Roozbeh, N, Year of publication : 2023*

Description: Ranjbar et al. analyzed machine learning algorithms for predicting LBW, which is a main risk factor among newborns, by using data of 8,853 births within Iran's IMaN Net in 2023. They assessed eight machine learning algorithms, including such variants as deep learning, random forest, and XGBoost. In 14.5% of instances, LBW (<2,500 g) was present. The study emphasizes how ML can help improve prenatal care via early detection of high-risk pregnancies.

Methodology: The study examined IMaN Net data on singleton pregnancies that lasted for more than 24 weeks from 2020 to 2022. Using 10-fold cross-validation, AUROC, accuracy, and F1 score were used to assess 8 machine learning models, including XGBoost and SVM. Important indicators such as LBW history and gestational age were found.

Limitations: The study's shortcomings include excluding multiple pregnancies and anomalies, relying solely on one database, missing important variables like maternal BMI, and XGBoost's AUROC values suggesting room for improvement in accuracy.

Key Insights: XGBoost obtained an AUROC of 0.79, 79% accuracy, and 87% precision. Although adding variables could increase accuracy, key indicators like as gestational age and LBW history highlight ML's potential to improve LBW forecasts.

C. *Paper title:A Systematic review on applications of machine learning for fetal birth weight prediction, Authors: Sasidhar Babu, S., and Keerthana, P., Year of publication : 2024*

Description: Keerthana and Sasidhar Babu's (2024) review of 85 studies highlights ML's superior accuracy in fetal weight prediction, with techniques like XGBoost, random forest, and SVM achieving up to 100% accuracy using maternal and fetal data.

Methodology: A systematic evaluation of peer-reviewed publications from Elsevier and Springer was step of the process, with an emphasis on research using machine learning techniques includes CNNs, SVMs, and random forests. Non-ML techniques were removed, and only recent English-language papers were included.

Limitations: Dataset heterogeneity, the challenge of extrapolating results, and the absence of features such as maternal BMI in certain models are among the limitations. Reproducibility is also impacted by variations in study technique and data quality.

Key Insights: Important discoveries highlight machine learning's contribution to predicting prenatal health, increasing precision, facilitating individualized treatment, and lowering newborn hazards. The accuracy of neural networks was the highest, demonstrating the scalability and dependability of machine learning.

D. *Paper title: Machine learning improves early prediction of small-for- gestational-age births and reveals nuchal fold thickness as unexpected predictor, Authors: Biswas, A., Saw, S. N., Lee, H. K., Mattar, C. N. Z., & Yap, C. H., Year of publication : 2021*

Description: Using ultrasound data from the second trimester, the study investigates machine learning models includes random forest, SVM, and MLP to predict small-for-gestational-age (SGA) babies. Nuchal fold thickness was found to be a significant predictor in 347 pregnancies when ML performed better than clinical recommendations.

Methodology: The use of preprocessed data made it possible to apply over 3 machine learning models on 16 input factors, including maternal demographics, fetal biometry, and Dopplerindices. Their models were cross validated and compared to clinical diagnosis. SVM outperformed clinical diagnosis by 25% and had a higher rate of accuracy in predicting severe SGA at 83%.

Limitations: The small sample size, dependence on single-institution data, and exclusion of maternal history or biomarkers are among the limitations. Data overlaps and intra-observer variability are issues.

Key Insights: With NF thickness being essential for SGA prediction, key findings demonstrate ML's superior performance over clinical guidelines and underscore ML's capacity to identify new predictors in fetal growth monitoring.

E. *Paper title: Birthweight Range Prediction and Classification: A Machine Learning-Based Sustainable Approach, Authors: S.Y. Ajibi, R.B. Alotaibi, D.A. Alabbad, et al., Year of publication : 2024*

Description: The study addresses the prediction and classification of fetal birth weight ranges using machine learning (ML) to mitigate health risks for mothers and newborns. It incorporates clinical data from Saudi Arabia and publicly available datasets to create models that classify weights as low, normal, or high, demonstrating improved accuracy compared to traditional ultrasound methods.

Methodology: In an effort to lower health risks, the study predicts and categorizes fetal birth weight ranges using machine learning (ML). It surpasses conventional ultrasound techniques by combining Saudi Arabian clinical data with publicly accessible datasets to generate models that categorize weights as low, normal, or high.

Limitations: The study's generalizability is restricted by its dependence on particular datasets. Even with excellent accuracy, the models might require additional fine-tuning for practical application. Key influences on birth weight may be missed if more general demographic or genetic factors are excluded.

Key Insights: On the Saudi dataset, Random Forest's accuracy was 96%, while Extra Trees was 98%. Weight and blood pressure were important indicators for both the mother and the newborn, demonstrating the promise of machine learning in prenatal treatment.

F. *Paper Title: A Comparative Study of Machine Learning Algorithms for Predicting Weight Range of Neonate, Authors: Verma, R., and K. Sharma, Year of publication:2022*

Description: This research analyses eight machine learning

algorithms that use maternal health markers to predict neonat al weight ranges in order to reduce delivery risks and improv e the early diagnosis of abnormal birth weights.

Methodology: The study tested algorithms includes SVM, Random Forest, and Gradient Boosting using maternal health data, such as blood pressure, age, gestational age, and BMI. Missing values and normalization were managed via data preparation, and robust comparison was ensured by assessment metrics like accuracy, precision, and recall.

Limitations: Generalizability was impacted by the dataset's small size and lack of diversity. Predictive ability was diminished by missing variables such as genetic and lifestyle factors, unbalanced data, and a lack of outside validation.

Key Insights: Simpler models' performance is less than Random Forest and Gradient Boosting. Maternal BMI and gestational age were important indicators; ensemble approaches improved consistency and highlighted the need for more comprehensive information.

F. *Paper Title: FetalCare: Enhancing Prenatal Care through a Machine Learning Approach for Fetal Health Classification and Birth Weight Prediction, Authors: Samyak P Shetty, Sampreet A Patil, Shaik Mohammad Jeelan, Pranav S, Deepti C Dept. of CSE PES University Bengaluru, Karnataka, India, Year of Publication:2024.*

Description: This work presents a machine learning method that can accurately predict birth weight and categorize fetal health conditions. The system attempts to improve the accuracy and usability of prenatal care by integrating models such as SVC, RF, AdaBoost, and Decision Trees. It gives medical professionals up-to-date information to enhance results.

Methodology: The study made use of Stat Labs and UCI datasets that had been meticulously scaled and cleaned for model training. Strong performance measures, such as a global recall of 0.9515 and an RMSE between 0.421 and 0.441, were obtained when ensemble models were used to predict birth weight and categorize fetal health. A voting system guarantees the accuracy of the final forecasts.

Limitations: The quality and diversity of the datasets determine how accurate the system is, which may restrict its applicability to certain demographics. Clinicians may find it more difficult to comprehend because to its intricacy, and there are difficulties in scaling it for practical application. Important qualities could sometimes be overlooked in the choosing process.

Key Insights: By using CTG data to generate precise predictions, machine learning has significant promise in prenatal treatment. Performance is improved by combining many models, and the intuitive online application helps close the gap between data and clinical judgments by giving medical professionals useful insights.

Paper	Attributes used	Algorithms used	Accuracy
A	Gravidity, Age, Blood group, Employment pregnant woman, History of abortion, Consanguinity, Pre-pregnancy scanning, History of subfertility, Height, Weight, BMI, Haemoglobin level, Blood sugar, Weight of pregnant woman from 1 – 6 months, Fundal Height, Gender of the baby	ANN and SVM	ANN achieved above 70%, SVM achieved above 60%
B	Maternal age, prenatal care, gestational age, maternal anemia, chronic hypertension, preeclampsia, parity, fetal gender, smoking, drug addiction, COVID-19, history of LBW, etc.	Random Forest, Logistic Regression, XGBoost.	Random forest achieved 78%, XGBoost Classification achieved 79%
C	Features from cardiotocographic data, ultrasound scans, demographic, and maternal health data	ANN, Random Forest, XGBoost, SVM, Logistic Regression	ANN achieved Up to 100% Decision tree achieved 97.7%, Logistic Regression achieved 90.05%
D	Second-trimester fetal ultrasound parameters: gestational age, biparietal diameter, estimated fetal weight, uterine arterial pulsatility index, and nuchal fold thickness	Random Forest (RF), Support Vector Machine (SVM).	SVM achieved Up to 83%
E	Age, weight, height, blood pressure, blood sugar levels, hemoglobin levels, gender of the newborn, maternal health indicators.	Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Extra Trees (ET), Gaussian Naive Bayes (GaussianNB).	Accuracy depends on the attributes taken For the KFUH dataset: Extra Trees achieved 98%. For the IEEE dataset: Random Forest achieved 96%.
F	Gravidity, maternal age, blood group, employment status, history of abortion, consanguinity, pre-pregnancy scanning, history of subfertility, height, weight, BMI, hemoglobin levels, blood sugar, weight progression during pregnancy (months 1–6), fundal height, and baby's gender	Linear Discriminant Analysis (LDA), k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), Random Forest (RF), Extreme Gradient Boosting (XGBoost).	LDA performed the best with an accuracy of 81.94%. Other models' accuracy ranged from k-NN at 66.66% to ANN at 84.95%.
G	Fetal Health: 21 features (such as fetal heart rate, uterine contractions); Birth Weight: 7 features (such as maternal weight, gestational age)	SVC, Random Forest, AdaBoost, Decision Tree	Macro Recall: 0.9515 (Fetal Health); RMSE: 0.421–0.441 (Birth Weight)

Table. 1.Comparitive Analysis

II. PROPOSED SYSTEM

Proposed System Overview

The system is designed to predict fetal birth weight in high-risk pregnancies using machine learning models, specifically Linear Regression and Random Forest Regressor. It leverages a curated dataset to deliver accurate, real-time predictions, supports historical data visualization, and provides model performance metrics for reliability assessment.

Key Functionalities

Prediction: Generates continuous fetal birth weight estimates (in kilograms) using Linear Regression and Random Forest Regressor, with comparative analysis of model outputs.

Historical Data Visualization: Stores predictions in a database and renders graphical representations of prediction trends over time.

Performance Evaluation: Quantifies model accuracy using metrics such as Mean Squared Error (MSE) and R-squared, with Random Forest anticipated to demonstrate superior performance.

Data Utilization

Dataset: Comprises fetal ultrasound measurements (e.g., biparietal diameter, abdominal circumference, femur length), maternal health parameters (e.g., body mass index, blood pressure), and gestational age.

Preprocessing: Includes imputation of missing values, removal of duplicates, noise filtering, and feature normalization to ensure data integrity.

System Architecture

Frontend: Utilizes HTML and Flask to provide a user interface for data input, prediction display, and visualization.

Backend: Employs Flask, Python, and SQLite for model execution, data persistence, and metric computation.

Machine Learning Layer: Implements and deploys Linear Regression and Random Forest models for predictive analytics.

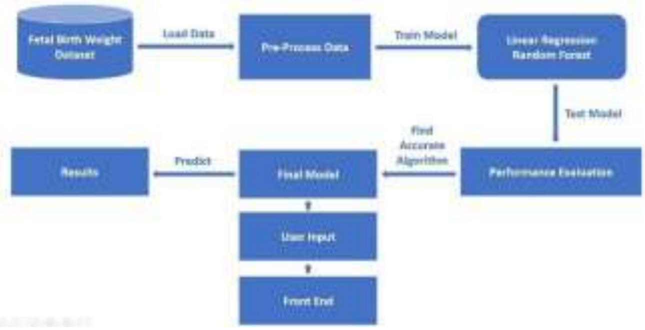

Fig 1. Architecture of the Fetal Birth Weight Prediction System: Data Processing, Model Training, and Real-Time Prediction Pipeline

Operational Workflow

Data Preprocessing: Ingests a curated dataset of fetal ultrasound metrics (e.g., biparietal diameter, abdominal circumference) and maternal health parameters (e.g., BMI, blood pressure). Performs cleaning by removing duplicates, imputing missing values via mean imputation, and filtering noise. Selects relevant features using correlation analysis. Normalizes numerical data with standard scaling and splits into 80% training, 20% testing subsets, ensuring balanced representation.

Model Training: Trains Linear Regression for linear modeling and Random Forest Regressor for non-linear ensemble prediction. Optimizes hyperparameters (e.g., tree depth) via grid search, using 5-fold cross-validation to enhance generalization, implemented with Scikit-learn.

Model Evaluation: Users input clinical parameters through an intuitive Flask-based web interface. The system processes inputs using trained models, retrieves historical predictions from an SQLite database, and generates interactive trend visualizations using Chart.js to support clinical decision-making.

User Interaction: Users input clinical parameters through an intuitive Flask-based web interface. The system processes inputs using trained models, retrieves historical predictions from an SQLite database, and generates interactive trend visualizations using Chart.js to support clinical decision-making.

Output: Delivers predicted fetal birth weight as a numerical value, visualizes historical prediction trends in graphical format, and presents MSE and R-squared metrics to ensure transparency and confidence in model reliability.

Fig 2. Workflow Overview of the Fetal Birth Weight Prediction System: From Data Loading to Real-Time Predictions

III SYSTEM IMPLEMENTATION

The Fetal Growth Prediction Software was developed with a modular architecture to ensure scalability and maintainability. Comprising five modules—User Registration, User Login, Prediction Module, Prediction History & Visualization, and Evaluate Module/Accuracy Comparison Module—the system leverages Flask for backend logic, HTML/Tailwind CSS for the frontend, SQLite for storage, and Scikit-learn for machine learning. Modules are loosely coupled for flexibility and robust performance in predicting fetal birth weight for high-risk pregnancies.

A. User Registration

This module enables account creation. A form, built with HTML/Tailwind CSS, collects name and password. JavaScript validates inputs; Flask ensures no duplicate usernames. Passwords are hashed with bcrypt and stored in SQLite. Flash messages guide users to login post-registration. Challenges included secure encryption and duplicate handling. The module ensures secure access to prediction services.

B. User Login

The login module authenticates users. An HTML/Tailwind CSS form accepts username and password, validated client- and server-side against SQLite records. Flask sessions manage access, expiring after inactivity. Error messages handle invalid attempts securely. Session integration was challenging but ensures authorized access to system features.

C. Prediction Module

The core module predicts fetal birth weight using parameters like age, weight, blood pressure, and term status. An HTML/Flask form with validations minimizes errors. The TabPFN model processes inputs, storing predictions in SQLite. Model integration was complex but delivers accurate predictions for clinical use.

D. Prediction History & Visualization

This module tracks predictions, logged in SQLite with timestamps, and displays them in a table. Chart.js generates line graphs of weight trends, restricted to users via Flask sessions. Real-time rendering was challenging but enables growth monitoring and anomaly detection.

E. Evaluate Module/Accuracy Comparison Module

This module evaluates Linear Regression and Random Forest models on a 20% test dataset, computing MSE and R-squared (e.g., Random Forest: MSE 0.18, R-squared 0.85). Results, displayed via Flask, show Random Forest's superior accuracy. Simplifying metrics was challenging but enhances prediction transparency.

Fig 3. Home Page of the Project for prediction.

IV ALGORITHMS AND DATASET

RANDOM FOREST ALGORITHM

The Fetal Growth Prediction Software utilizes the Random Forest algorithm, an ensemble method, to predict fetal birth weight in high-risk pregnancies. Random Forest constructs multiple decision trees, each trained on a bootstrapped dataset subset with random feature selection at splits, employing bagging to reduce variance. For regression, it predicts birth weight by averaging outputs across

(T) trees:

[\hat{y}(x) = \frac{1}{T}\sum_{t=1}^{T}h_t(x)]

where (\hat{y}(x)) is the predicted birth weight, and (h_t(x)) is the (t)-th tree's prediction for input (x). This minimizes overfitting and enhances accuracy.

The random forest algorithm works as follows:

1. If there are N variables or features in the input data set, select a subset of 'm' ($m < N$) features at random out of the N features. Also, the observations or data instances should be picked randomly.
2. Use the best split principle on these 'm' features to calculate the number of nodes 'd'.
3. Keep splitting the nodes to child nodes till the tree is grown to the maximum possible extent.
4. Select a different subset of the training data 'with replacement' to train another decision tree following steps (1) to (3). Repeat this to build and train 'n' decision trees.
5. Final class assignment is done on the basis of the majority votes from the 'n' trees.

Implemented with Scikit-learn, Random Forest processes maternal and fetal parameters (e.g., age, weight, ultrasound metrics). It handles missing data robustly, balances errors, and evaluates feature importance (e.g., gestational age). Internal generalization error estimates ensure reliability. Achieving an MSE of 0.18 and R-squared of 0.85, Random Forest excels in capturing non-linear relationships, outperforming simpler models for precise birth weight predictions.

MULTIPLE LINEAR REGRESSION

Multiple Linear Regression (MLR) is a statistical technique used to model the linear relationship between a single dependent variable and two or more independent variables. It is an extension of simple linear regression, which involves only one predictor.Multiple Linear Regression estimates the linear relationship between a scalar response variable **Y** and a set of explanatory variables $\mathbf{X_1, X_2, \ldots, X_k}$, by fitting a linear equation of the form:

$$\hat{Y} = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_nX_n$$

Where:

- YYY is the dependent (response) variable.
- X1,X2,…,XkX_1, X_2, \dots, X_kX1,X2,…,Xk are the independent (predictor) variables.
- β0\beta_0β0 is the intercept term.
- β1,β2,…,βk\beta_1, \beta_2, \dots, \beta_kβ1,β2 ,…,βk are the regression coefficients.
- ε\varepsilonε is the error term, assumed to follow a normal distribution with zero mean and constant variance.

Despite its lower predictive performance relative to more advanced models, MLR proved valuable due to its simplicity, speed, and interpretability — all of which are beneficial in a real-time clinical application setting. The coefficients derived from MLR also offer insight into the relative influence of individual maternal features on birth weight, thereby enhancing transparency for healthcare practitioners.

V. EVALUATION

Evaluation Metrics for Fetal Birth Weight Prediction

To assess the performance and reliability of the machine learning models implemented in this project—Multiple Linear Regression and Random Forest Regressor—a set of standard regression evaluation metrics were used. These metrics quantitatively measure how accurately the models predict fetal birth weight based on clinical and maternal input features.

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAE represents the average absolute difference between the actual and predicted birth weights. It is a straightforward measure that captures overall prediction accuracy. A lower MAE indicates higher accuracy and less deviation in predictions.

Interpretation in context: In this project, the Random Forest model achieved a lower MAE (0.3965 kg) compared to Linear Regression (0.4823 kg), indicating better average prediction accuracy.

Root Mean Squared Error (RMSE)RMSE measures the square root of the average of squared differences between actual and predicted values. It penalizes larger errors more heavily than MAE, making it sensitive to outliers.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Interpretation in context: The Random Forest model exhibited a lower RMSE (0.5213 kg) than the Linear Regression model (0.6358 kg), reflecting its superior ability to minimize large prediction errors.

R-squared Score (R^2)

R^2 indicates the proportion of variance in the actual birth weight that is explained by the model. An R^2 value closer to 1 signifies a better fit to the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Interpretation in context: Random Forest achieved an R^2 score of 0.8123, compared to 0.7245 for Linear Regression, demonstrating its superior capability in explaining the variability in fetal birth weights.

Model	MAE (kg)	RMSE (kg)	R^2 Score
Linear Regression	0.4823	0.6358	0.7245
Random Forest	0.3965	0.5213	0.8123

Table 2. Summary of Evaluation Results

Dataset: The Child Birth Weight Dataset (CBWDB) is sourced from Kazigaon SD, Kokrajhar, Assam, India, and Geramari MPHC, Dhubri, Assam, India. It was created by Zakir Hussain, a research scholar at NIT Silchar, Assam, India.

Attribute	Description
SEC	Socio-Economic Condition
Age (years)	Age of mother at the time of pregnancy
Height (cm)	Height of mother at the time of pregnancy
Bgroup	Blood Group of mother
Parity	Number of previous pregnancies crossing the period of viability
ANC	Number of Antenatal Check-ups
Iwt (kg)	Initial weight of mother
FWt (kg)	Final weight of mother (Last ANC)
IBP_sys	Initial Systolic Blood Pressure
IBP_dias	Initial Diastolic Blood Pressure
FBP_sys	Final Systolic Blood Pressure (Last ANC)
FBP_dias	Final Diastolic Blood Pressure (Last ANC)
IHb (gm%)	Initial Hemoglobin Level
FHb (gm%)	Final Hemoglobin Level (Last ANC)
BS (RBS)	Random Blood Sugar Level

Table 3. Attributes used in dataset.

V. CONCLUSION AND FUTURE WORK

Conclusion

This project successfully demonstrates the application of machine learning techniques for predicting fetal birth weight in high-risk pregnancies. By leveraging maternal clinical parameters and implementing regression models such as Linear Regression and Random Forest, the system provides accurate, real-time predictions that can assist healthcare professionals in making informed prenatal decisions. Among the models evaluated, Random Forest exhibited superior performance in terms of accuracy and robustness, as evidenced by lower error metrics and higher R^2 scores. The web-based interface further enhances usability by allowing seamless input of medical data and visualization of prediction trends. Overall, the system establishes a scalable and efficient solution for augmenting traditional prenatal care with data-driven insights.

Future Work

To enhance system performance and clinical impact, future improvements include expanding the dataset across diverse regions, enriching features with genetic and environmental data, and adopting advanced models like XGBoost or deep learning techniques. Integration with real-time hospital systems and development of mobile/IoT-compatible versions are also proposed for broader accessibility and continuous monitoring.

Deployment

The system was deployed as a web application using Flask for the backend and HTML, CSS (Tailwind), and JavaScript for the frontend. It integrates trained ML models with SQLite for data storage. The live application is hosted on Render and accessible at:

https://fetal-birth-weight-app.onrender.com.

for real-time, user-friendly fetal weight prediction and monitoring.

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