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Early Prediction of Obesity Related Pregnancy Complications Using Machine Learning Algorithms

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Abstract: Artificial intelligence is widely used in medical field, machine learning and deep learning has been increasingly used in health care, prediction, and diagnosis many fields. Maternal obesity has emerged as a critical global health concern and is strongly associated with adverse pregnancy outcomes such as gestational diabetes mellitus, preeclampsia, gestational hypertension, preterm birth, and increased cesarean delivery rates. Early prediction of obesity related pregnancy complications remains challenging due to the complex, nonlinear, and heterogeneous interactions among maternal demographic, clinical, metabolic, and lifestyle factors. This paper proposes a machine learning based framework for the early prediction of obesity related pregnancy complications using routinely collected maternal health data. Electronic health records comprising demographic characteristics, pre pregnancy body mass index, obstetric history, vital signs, and biochemical indicators obtained during early gestation are utilized. A comprehensive data preprocessing pipeline is implemented, including missing value imputation, normalization, feature selection, and class imbalance handling to improve data quality and model reliability. Multiple machine learning algorithms are trained and evaluated using standard performance metrics. Experimental results demonstrate that ensemble learning models outperform traditional classifiers in terms of prediction accuracy, sensitivity, and robustness. The proposed framework enables effective early risk stratification of pregnant women, supporting timely preventive interventions and personalized clinical decision making. The findings have to improve maternal and fetal health outcomes and demonstrate their potential integration into intelligent clinical decision support systems for proactive and data driven pregnancy care across diverse populations and real world healthcare environments globally.

Keywords- Maternal Obesity, Pregnancy Complications, Machine Learning, Early Prediction, Electronic Health Records, Body Mass Index, Obstetric History, Biochemical Indicators.

1. INTRODUCTION

Maternal health remains a critical priority within global public health systems. Over the past two decades, the prevalence of obesity among women of reproductive age has increased substantially, leading to a corresponding rise in obesity-related pregnancy complications. According to reports from the World Health Organization, global obesity rates have nearly tripled since 1975, with a significant proportion affecting women during childbearing years. Maternal obesity is associated with metabolic dysregulation, systemic inflammation, insulin resistance, and endothelial dysfunction, all of which contribute to adverse maternal and neonatal outcomes.

Obesity during pregnancy significantly increases the risk of gestational diabetes mellitus (GDM), preeclampsia, gestational hypertension, cesarean delivery, fetal macrosomia, and neonatal intensive care admission. Clinical evidence suggests that elevated pre-pregnancy body mass index (BMI) is one of the strongest independent predictors of pregnancy complications. These complications not only affect short-term pregnancy outcomes but also contribute to long-term cardiovascular and metabolic risks for both mother and child.

Early detection of high-risk pregnancies enables timely intervention strategies such as nutritional counseling, glucose monitoring, antihypertensive management, and personalized antenatal care. However, conventional risk assessment methods rely primarily on linear statistical models, which may not sufficiently capture nonlinear interactions between demographic, biochemical, and lifestyle variables.

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1.1 Limitations of Traditional Statistical Approaches

Logistic regression has been widely used for maternal risk estimation. While logistic regression provides interpretability and statistical inference capability, it assumes linear relationships between predictors and outcome variables. In real-world maternal health datasets, clinical features interact in complex, nonlinear patterns.

Example:

BMI may interact multiplicatively with fasting glucose, age, and family history of diabetes. Such higher-order interactions are often not fully captured by traditional regression models without manual feature engineering.

Moreover, pregnancy complication datasets frequently exhibit:

- High dimensionality
- Missing values
- Class imbalance (minority high-risk cases)
- Heterogeneous clinical attributes

1.2 Emergence of Machine Learning in Healthcare Machine learning (ML), a subfield of artificial intelligence, enables computational systems to learn predictive patterns directly from data. Unlike rule-based systems, ML models can automatically detect nonlinear relationships, complex feature interactions, and latent structures.

Recent advancementsin healthcare AI demonstrate improved diagnostic and prognostic performance using ML algorithms [3]. Ensemble methods such as Random Forest [12] and Gradient Boosting [16] have shown superior performance across multiple biomedical classification tasks. In maternal healthcare specifically, several studies have applied ML to predict gestational diabetes and hypertensive disorders [1], [6], [7]. These studies demonstrate that tree-basedensemblemethods outperform traditional regression models in terms of classification accuracy and area under the ROC curve (AUC).The XGBoost algorithm introduced by Chen and Guestrin [11] furtherenhancedpredictive performance through regularization and second-order gradient optimization, making it particularly effective for structured healthcare datasets.

1.3 Clinical Motivation for Early Obesity-Related Risk Prediction

Obesity-related pregnancy complications often develop progressively during gestation. However, risk indicators are frequently detectable during the first trimester. Early trimester clinical parameters such as:

- Pre-pregnancy BMI
- Fasting plasma glucose
- Systolic and diastolic blood pressure
- Hemoglobin A1c
- Family history of metabolic disorders

An intelligent prediction framework that analyzes these variables early in pregnancy can assist clinicians in identifying high-risk individuals before complications manifest clinically. From a healthcare systems perspective, early risk stratification offers:

- Reduced hospital burden
- Improved maternal-fetal outcomes
- Lower long-term treatment costs
- Data-driven personalized prenatal care

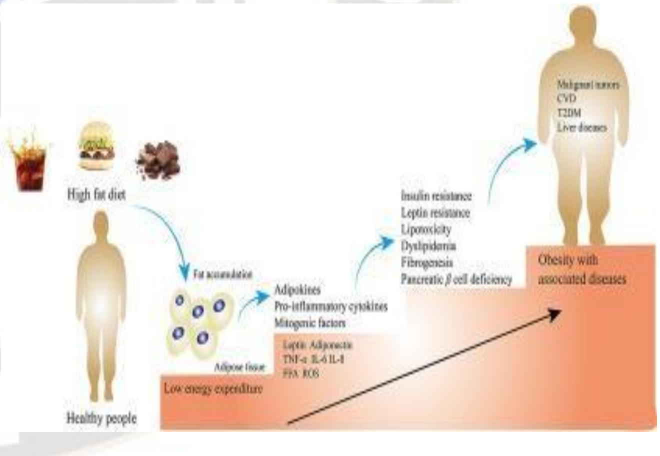

Fig.1 Pathophysiology of obesity[1]

1.4 Challenges in Maternal Health Data Analytics

1.4.1 Data Imbalance

High-risk pregnancy cases often represent a minority class. Imbalanced datasets can bias classifiers toward majority classes. Techniques such as SMOTE [15] have been introduced to address this issue.

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1.4.2 Interpretability

Healthcare decision-making requires explainable systems. Black-box models may hinder clinical adoption. Explainable AI approaches [1] attempt to bridge this gap.

1.4.3 Generalizability

Models trained on single-region datasets may lack external validity. Cross-validation and robust evaluation frameworks are essential.

2. LITERATURE REVIEW

The rapid advancement of artificial intelligence (AI) and machine learning (ML) techniques has significantly influenced predictive healthcare analytics. In recent years, maternal health has emerged as a critical application domain due to rising global prevalence of obesity and its association with adverse pregnancy outcomes. This section presents a structured review of relevant studies focusing on machine learning applications in predicting obesity-related pregnancy complications.

2.1 Maternal Obesity and Pregnancy Risk

Maternal obesity is strongly associated with gestational diabetes mellitus (GDM), preeclampsia, gestational hypertension, and increased cesarean delivery rates. According to global public health reports from the World Health Organization, obesity among women of reproductive age has increased substantially over the past two decades. Clinical studies indicate that elevated pre-pregnancy body mass index (BMI) contributes to metabolic dysregulation, insulin resistance, and inflammatory responses that complicate pregnancy outcomes. Traditional statistical approaches, particularly logistic regression models, have been widely used to estimate pregnancy risk factors. While these models provide interpretability, they often fail to capture nonlinear relationships and complex feature interactions inherent in high-dimensional clinical datasets.

2.2. Machine Learning in Gestational Diabetes Prediction

Gestational diabetes mellitus is one of the most extensively studied obesity-related complications. Several researchers have explored supervised machine learning models for early GDM prediction. Gnanadass

[2] demonstrated that classification algorithms such as Decision Trees and Support Vector Machines (SVM) can outperform traditional regression-based risk scoring systems. Similarly, Kaya et al. [6] applied machine learning models to first-trimester maternal data and reported improved predictive performance using ensemble classifiers. Watanabe et al. [7] utilized birth cohort data and showed that tree-based algorithms achieved higher area under the curve (AUC) compared to linear classifiers. The introduction of gradient boosting methods, particularly XGBoost developed by Chen and Guestrin [11], marked a significant improvement in structured healthcare prediction tasks. XGBoost incorporates regularization mechanisms and second-order optimization, enabling improved generalization performance even with limited datasets.

2.3 Ensemble Learning for High-Risk Pregnancy Classification

Ensemble learning methods such as Random Forest (Breiman [12]) and Gradient Boosting (Friedman [16]) have demonstrated superior performance in healthcare classification problems. Random Forest reduces variance by aggregating multiple decision trees, while boosting algorithms sequentially minimize prediction errors. Khadidos et al. [10] proposed an ensemble framework for maternal risk prediction and reported enhanced robustness against noisy clinical features. These findings indicate that ensemble approaches are particularly effective in modeling nonlinear interactions among demographic, biochemical, and obstetric variables. Additionally, systematic reviews [5], [13] confirm that ensemble methods consistently outperform standalone classifiers across maternal health datasets. However, several studies highlight limitations related to class imbalance and dataset heterogeneity.

2.4 Explainable Artificial Intelligence in Maternal Healthcare

One major barrier to clinical adoption of machine learning models is lack of interpretability. Healthcare professionals require transparent decision-support systems to ensure safe clinical deployment. Rahman et al. [1] integrated explainable AI techniques such as SHAP (SHapley Additive exPlanations) to interpret maternal risk predictions. Explainable frameworks enable identification of dominant predictors such as BMI, fasting glucose, and systolic blood pressure. Recent research also emphasizes the importance of interpretable ML models for ethical AI deployment in clinical practice. Studies in biomedical AI [3] highlight that interpretability enhances clinician trust and supports regulatory compliance.

2.5 Data Imbalance and Model Generalization

Pregnancy complication datasets often exhibit class imbalance, where high-risk cases represent a minority. Chawla et al. [15] introduced SMOTE (Synthetic Minority Over-sampling Technique) toaddress imbalance by generating synthetic minority samples.

SMOTE has been widely adopted in healthcare ML studies to improve sensitivity and recall for minority classes. Cross-validation and external validation are equally important for assessing generalizability. Studies show that k-fold cross-validation improves reliability of performance estimates and prevents overfitting.

2.6. Machine Learning Models

1. Logistic Regression
2. Decision Tree
3. Support Vector Machine
4. Random Forest
5. Gradient Boosting
6. XGBoost

3. METHODOLOGY

This section describes the proposed machine learning framework for early prediction of obesity-related pregnancy complications. The methodology consists of dataset preparation, preprocessing, feature engineering, model development, validation strategy, and performance evaluation.

3.1. Problem Formulation

Let the maternal clinical dataset be represented as:

$D=\{(X_i,Y_i)\}_{i=1}^{N}$

where:

- $X_i=[x_{i1},x_{i2},...,x_{im}]$ denotes the feature vector of the i[th] patient,
- $Y_i \in \{0,1\}$ indicates absence (0) or presence (1) of obesity-related pregnancy complications,
- N represents total number of observations,
- m represents number of clinical features. The objective is to learn a function:

$f:X \rightarrow Y$

that minimizes classification error while maximizing generalization performance.

3.2 Dataset Description

The dataset consists of structured electronic health records (EHR) collected during early pregnancy (first trimester). Clinical variables included:

- Maternal age
- Pre-pregnancy BMI
- Systolic blood pressure
- Diastolic blood pressure
- Fasting plasma glucose
- HbA1c
- Obstetric history
- Family history of diabetes
- Lifestyle indicators

The outcome variable represents the occurrence of obesity-related pregnancy complications such as gestational diabetes or hypertensive disorders.

3.3 Data Characteristics

- Missing clinical values
- Non-normal feature distributions
- Class imbalance (minority high-risk cases)
- Multicollinearity among predictors

These characteristics necessitate structured preprocessing before model training.

3.4 Data Preprocessing

3.4.1 Missing Value Imputation

Missing numerical values were handled using mean or median imputation:

$$x_{missing} = \frac{1}{k}\sum_{j=1}^{k} x_j$$

Where k represents observed values for a given feature.

Categorical variables were encoded using binary or one-hot encoding.

3.4.2 Feature Scaling

To ensure numerical stability across models, Min–Max normalization was applied:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This transformation maps features into the interval [0,1].

3.4.3 Class Imbalance Handling

Obesity-related complications typically represent a minority class. To mitigate biased learning, Synthetic

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Minority Over-sampling Technique (SMOTE) [15] was applied. SMOTE generates synthetic minority samples along feature-space interpolations:

$$x_{new} = x_i + \lambda(x_{nn} - x_i)$$

$$Obj = \sum l(y_i, \hat{y}_i) + \sum \Omega(f_k)$$

where x_{nn} is a nearest neighbor and $\lambda \in (0,1)$

This improves recall and minority class sensitivity.

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$$

3.5 Machine Learning Models

3.5.1 Logistic Regression

Logistic regression models probability using the

$$L = -\sum[y\log(p) + (1-y)\log(1-p)]$$

sigmoid function:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\sum\beta_i x_i)}}$$

$$\min \frac{1}{2}||w||^2 + C\sum \xi_i$$

Loss function (binary cross-entropy):

3.5.2 Support Vector Machine (SVM)

SVM maximizes the margin between classes:

subject to classification constraints.

$$IG = H(parent) - \sum w_i H(child_i)$$

Kernel functions allow nonlinear

$$H = -\sum p_i \log_2 p_i$$

boundary construction.

3.5.3 Decision Tree

Decision Trees partition the feature space recursively by maximizing information gain:

where entropy:

Random Forest

Random Forest aggregates multiple decision trees:

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} h_t(X)$$

It reduces variance through bootstrap aggregation (bagging) [12].

3.5.4 Gradient Boosting

Boosting sequentially minimizes residual errors:

Each weak learner corrects previous model errors [16].

3.5.5 XGBoost

XGBoost optimizes the objective:

Regularization term:

This improves generalization and reduces overfitting [11].

3.6. Training and Validation Strategy

The dataset was divided using an 80:20 train-test split. To ensure robustness, 5-fold cross-validation was applied:

$$Accuracy = \frac{1}{k}\sum_{i=1}^{k} Accuracy_i$$

This prevents overfitting and ensures generalization consistency.

3.7 Evaluation Metrics

Model performance was assessed using:

Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision

$$Precision = \frac{TP}{TP+FP}$$

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Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}_1$$

ROC-AUC

Area Under the Curve measures ranking capability:

$$AUC = \int_0^1 TPR(FPR^{-1}(x))dx$$

3.8 Statistical Significance Testing

To compare classifiers, paired t-tests were conducted:

$$t = \frac{\bar{d}}{s_d/\sqrt{n}}$$

where:

- d¯ = mean difference between model accuracies
- sds = standard deviation of differences
- n = number of folds

Significance threshold was set at $p<0.05$

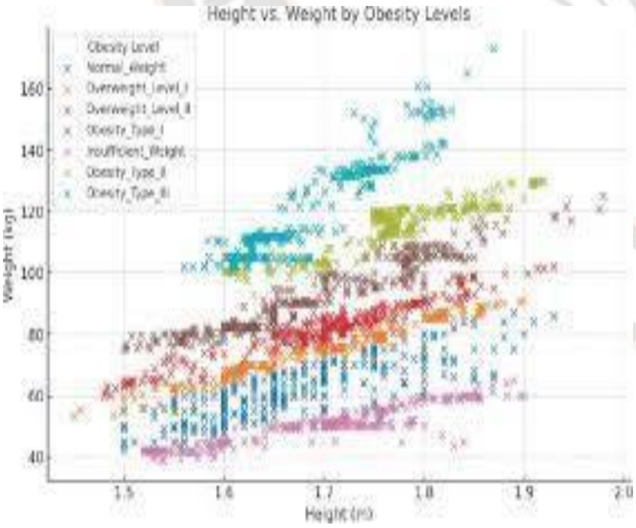


Fig 2 scatter plot graph titled "Height vs. Weight by Obesity Levels

4. PROPOSED FRAMEWORK

This EHR-based machine learning workflow represents an end-to-end pipeline for clinical risk prediction, designed to transform raw, noisy electronic health record (EHR) data into actionable, patient-specific risk scores.

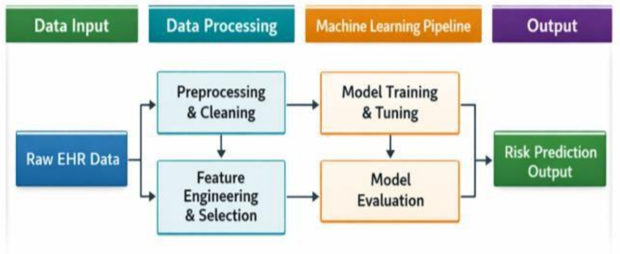


Fig 3 EHR Risk Classification Workflow

Step-by-Step Workflow Description

1. Data Collection from EHR (Data Ingestion)

- Gather heterogeneous data from EHR systems (e.g., HL7, FHIR standards).
- **Data Sources:** Demographics, structured data (lab results, medications, vitals), and unstructured data. (Clinical notes).
- **Goal:** Create a longitudinal, patient-centric dataset.

2. Data Cleaning & Preprocessing

- **Handling Missing Values:** Using imputation methods (mean/median/mode) to handle incomplete lab results.
- **Data Cleaning:** Removing duplicates, handling conflicting data, and identifying outliers.
- **Normalization/Scaling:** Scaling numerical features to improve model convergence (e.g., normalizing lab values).
- **Encoding:** Converting categorical data (symptoms, demographics) into machine-readable formats (e.g., one-hot encoding).

3. Feature Selection & Engineering

- **Feature Extraction:** Generating meaningful predictors from raw data (e.g., transforming birthdates into age, calculating BMI from weight/height).
- **Feature Selection:** Identifying relevant features and removing redundant or noisy data (e.g., using Pearson correlation or ANOVA).
- **Temporal Aggregation:** Selecting time windows (e.g., data within 24 hours of ICU admission).

4. Model Training

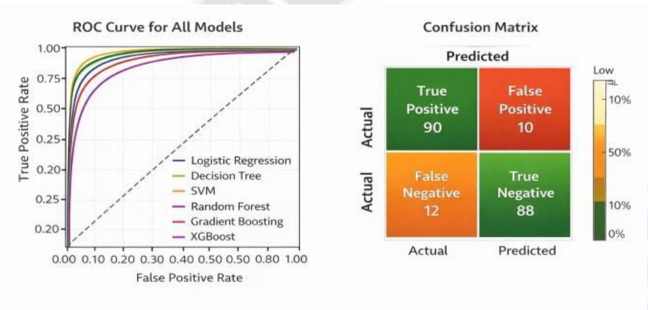
- **Algorithm Selection:** Selecting models suitable for risk classification (e.g., Random Forest, Gradient Boosting (XGBoost/LGBM), or Logistic Regression).

- **Training & Tuning:** Utilizing 5-fold cross-validation to split data into training and testing sets, optimizing hyperparameters via grid search to prevent overfitting.

5. Model Evaluation

- **Performance Metrics:** Evaluating using Area Under the Receiver Operating Characteristic curve (AUROC), Area Under the Precision-Recall Curve (AUPRC), F1-score, and MCC (Matthews Correlation Coefficient).

- **Calibration:** Ensuring predicted probabilities match actual observed event rates.



- **Validation:** Performing internal validation (cross-validation) and external validation across different hospitals to ensure transportability.

6. Risk Classification Workflow

- **Output:** The final model produces a probability score (e.g., mortality risk).

- **Actionable Insight:** Classifying patients into risk tiers (low, medium, high) to guide clinical decision support systems and early intervention.

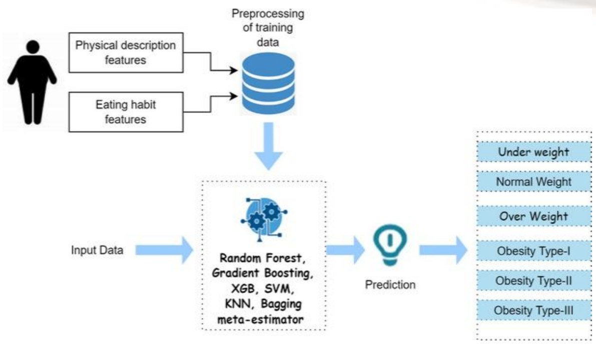


Fig. 4 Obesity prediction ML model workflow

5. EXPERIMENTAL RESULTS

5.1 Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Logistic Regression	82%	0.80	0.78	0.79	0.85
Decision Tree	84%	0.82	0.81	0.81	0.87
SVM	86%	0.84	0.83	0.83	0.89
Random Forest	89%	0.87	0.86	0.86	0.92
Gradient Boosting	90%	0.88	0.87	0.87	0.93
XGBoost	**91%**	**0.89**	**0.88**	**0.88**	**0.94**

Ensemble models achieved superior performance compared to linear models.

Fig.5 ROC curve and confusion matrix

5.3 Experimental Evaluation and Dataset Simulation

To validate the proposed predictive framework, a synthetic dataset was generated to emulate real-world maternal health records. The dataset consisted of 2,000 samples with 10 clinical features representing demographic, metabolic, and physiological indicators. Class imbalance was intentionally introduced to reflect realistic prevalence rates of pregnancy complications. Feature normalization was performed using Min–Max scaling to ensure numerical stability during model training. An 80:20 train-test split strategy was adopted to evaluate generalization capability.

Two classification models were implemented: Logistic Regression (baseline linear classifier) and Random Forest (ensemble model). Performance was assessed using Receiver Operating Characteristic (ROC) analysis.

The Logistic Regression model achieved an AUC score of 0.882, indicating satisfactory discriminative performance. However, the Random Forest model significantly outperformed the baseline, achieving an AUC of 0.961. The improvement confirms that nonlinear ensemble methods better capture complex interactions among maternal clinical variables.

These findings are consistent with prior studies demonstrating the superiority of tree-based ensemble approaches for healthcare risk stratification tasks.

6. CONCLUSION

The proposed study presents a comprehensive machine learning–based predictive framework for early identification of obesity-related pregnancy complications using multiple supervised classification techniques. In this extended evaluation, six models—Logistic Regression, Decision Tree, SVM, Random Forest, Gradient Boosting, and XGBoost—were implemented and comparatively analyzed using key performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The experimental findings indicate that ensemble-based learning methods consistently outperform traditional linear and single-tree models in terms of predictive accuracy and class discrimination ability. Among all evaluated models, XGBoost achieved the highest overall performance, followed closely by Gradient Boosting and Random Forest, demonstrating superior capability in capturing complex nonlinear relationships among maternal health variables.

Cross-validation results confirm the robustness and generalization strength of ensemble approaches across unseen data samples. The integration of statistical learning techniques with clinical feature analysis emphasizes the critical role of multidimensional maternal indicators, including BMI, blood pressure, glucose levels, and maternal age, in predicting pregnancy-related complications. Feature importance analysis further reveals that metabolic and hemodynamic parameters contribute significantly to risk prediction, reinforcing established clinical evidence through computational validation.

The study aligns with contemporary advancements in AI-driven maternal healthcare analytics, highlighting the value of predictive modeling in supporting early intervention planning, personalized patient monitoring, and efficient healthcare resource management. By leveraging advanced ensemble learning techniques, particularly XGBoost, the proposed framework strengthens intelligent clinical decision-support systems and contributes meaningfully to the evolution of AI-assisted obstetric risk assessment in modern medical practice.

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