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Research Article

Early Trimester Multi-Risk Prediction of Pregnancy Complications Using Explainable Ensemble Machine Learning

Adicherla Sai Chaithanya[1*], Vasavi Sravanthi Balusa[2], Gangishetti Yashwanth[3], Kandle Shashank[4] and Cheela Sameerraj[5]
[1,2,3,4,5]Department of Computer Science & Engineering, Methodist College of Engineering and Technology, Hyderabad, Telangana, India

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Correspondence*
adicherlachaithu@gmail.com

ORCID
Adicherla Sai Chaithanya
https://orcid.org/0009-0009-0191-9813
Vasavi Sravanthi Balusa
https://orcid.org/0000-0001-8642-2981
Gangishetti Yashwanth
https://orcid.org/0009-0000-3603-4788
Kandle Shashank
https://orcid.org/0009-0008-1907-169X
Cheela Sameerraj
https://orcid.org/0009-0006-0425-3250

Abstract

Pregnancy complications such as gestational diabetes, hypertension, anemia, and preeclampsia increase health risks for both mothers and their unborn children. Health professionals need to identify these risks during the first trimester because this period is the most critical timeframe for effective preventive measures. Current risk-assessment methods predict only one specific risk instead of providing complete evaluations of early-stage health conditions. This study aims to develop an explainable ensemble machine learning framework for early trimester multi-risk prediction of pregnancy complications. An ensemble of Random Forest, XGBoost, and Support Vector Machine algorithms was used to develop a predictive model. The model was trained using maternal health data gathered during the first few weeks of pregnancy. To improve interpretability, model-agnostic explainability methods such as SHAP and LIME were used to provide both global and local insights into the model's predictions. The proposed ensemble model achieved strong predictive performance, with an accuracy of 88%, a macro F1-score of 0.89, and a macro ROC-AUC of 0.967. The explainability analysis identified key clinical features influencing pregnancy risk, improving transparency and supporting clinical understanding. The proposed framework demonstrates the effectiveness of combining ensemble learning with explainable AI for early pregnancy risk assessment. It provides accurate and interpretable predictions, enabling healthcare professionals to make informed decisions and improve maternal healthcare outcomes.

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I. INTRODUCTION

Anemia, preeclampsia, gestational diabetes, and hypertensive disorders are common pregnancy risks. These risks are among the primary reasons pregnant women become ill or even pass away. Usually, these issues start developing during the first weeks of pregnancy. They can be difficult to detect until much later, when treatment is very limited and risks are considerably increased. It is of utmost importance to determine early whether a pregnancy is at risk so that doctors can monitor the woman closely, provide the necessary care to prevent problems, and, if necessary, intervene with medical help. When assessing high-risk pregnancies, doctors typically use standard methods that involve examining the woman's health record, her past pregnancies, and drawing on their own experience and expertise. Although this type of pregnancy risk assessment can be beneficial, it is not always flawless. Pregnancy risk assessment and pregnancy risks are interrelated. Doctors must be knowledgeable about pregnancy risks to carry out accurate pregnancy risk assessments. Though these methods have been extremely helpful and widely used in many instances, they are still subjective, time-consuming, and primarily aimed at identifying individual complications instead of providing a comprehensive multi-risk evaluation. It is essential to track data produced at distinct stages of pregnancy from multiple viewpoints. Fortunately,

computational tools are available that can identify hidden patterns and forecast the most prevalent risk factors [1].

The research described here is inspired by current pregnancy risk prediction methods, which have three main limitations. First, most previous research has focused on predicting one complication at a time, while in reality multiple pregnancy-related risks coexist and influence each other. A unifying multi-risk prediction system is therefore necessary to provide a thorough evaluation of maternal health. Second, most machine learning models use accuracy as the main evaluation metric, and most models cannot be explained, which is a critical factor in medical decision-making, where professionals need to interpret and trust the model's outcomes [2]. Third, the early detection of pregnancy complications has not been adequately researched, even though in practice it remains the best way to apply preventive measures and improve outcomes. This work presents a solution to these problems by proposing an explainable ensemble machine learning framework for multi-risk prediction of pregnancy complications in the early trimester. The proposed method is intended to provide improved predictive performance and robustness through an ensemble strategy that combines various base classifiers [3].

Furthermore, the integration of explainable artificial intelligence methods allows both global and instance-specific understanding of model predictions, thereby supporting transparency and clinical relevance. The main contributions of this research are threefold. The first is the development of a machine learning framework based on ensemble methods for the early prediction of multi-risk pregnancy complications in the first trimester, allowing the simultaneous assessment of various existing risks. The second is the execution of thorough model evaluation using multi-class performance metrics such as ROC-AUC and calibration analysis to ensure the robustness and reliability of predictions [2]. The third is the incorporation of explainable artificial intelligence techniques such as SHAP and LIME to provide both global and patient-specific interpretability, thereby improving transparency and gaining clinicians' trust [4].

II. LITERATURE REVIEW

Technological progress in machine learning and explainable AI has accelerated research on the automated assessment of maternal and fetal risks. Recent research has investigated various architectures, ranging from deep learning and feature-engineering pipelines to ensemble classifiers, while a more limited yet expanding body of work emphasizes interpretability (SHAP/LIME) and early-trimester screening.

A. Ensemble and Feature-Engineering Approaches for Maternal Risk Prediction

Raza *et al.* [5] showed that maternal health risk classification can be improved through learning and feature-engineering processes, enabling more accurate risk prediction. Their paper, published in PLOS ONE, used a method called DT-BiLTCN. This method combines decision trees, Bi-LSTM, and temporal convolutional networks to extract features and then uses classifiers such as SVM and RF to predict maternal health risks. The study focused on maternal health risk classification. The research utilized a public maternal dataset and exhibited strong per-class ROC results (with per-class ROC accuracy exceeding 94%), indicating that features created from various models can provide significant insights for subsequent classifiers. Raza *et al.* concentrated mainly on performance metrics and feature construction, providing little attention to post-hoc model interpretability or early-trimester-specific screening; thus, the study's approach inspires a supplementary framework that combines ensemble benefits with interpretable results for healthcare professionals.

B. Ensemble Frameworks Applied to Multi-Risk Maternal Classification

Khadidos *et al.* [1] developed a multi-ensemble pipeline for classifying maternal health risks that demonstrated the benefits of using different types of learners to improve robustness on real hospital datasets. They conducted an extensive study of different ensemble methods and reported that the overall performance of the ensembles was superior to that of the weakest base learners, demonstrating the importance of ensembles for noisy clinical data. Although the manuscript advances ensemble methods in this field, it gives greater priority to predictive accuracy than to explainability and early-trimester generalization—limitations that this work addresses by combining ensemble results with both global (SHAP) and local (LIME) explanations while targeting early pregnancy signals.

C. Explainable ML (SHAP) for Maternal and Fetal Monitoring

Innab *et al.* [6] introduced the LightGBM classifier for fetal and maternal health assessment, and the application of SHAP values provided evidence of the main predictors for each target outcome. Their workflow demonstrates that SHAP can transform model results into clinically interpretable feature rankings, increasing clinicians' confidence and supporting targeted interventions. The researchers employed class balancing (SMOTE) and highlighted the need for clear implementation justifications as one of the study's contributions. However, the research tends to concentrate on one or a few specific results (e.g., CTG-driven fetal classification) rather than an overall multi-risk early-warning system; thus, it reflects a demand for unified pipelines that produce both strong ensemble predictions and SHAP/LIME explanations for various maternal risks concurrently.

D. Early-Trimester Prediction and External Validation of ML Screening Models

The importance of early prediction is evident in validation studies such as that by Gil *et al.* [7], who evaluated a first-

trimester machine learning model for preeclampsia screening using a large PREVAL cohort. The outcomes show that ML techniques can deliver clinically beneficial first-trimester screening effectiveness comparable to existing competing-risks models, while also highlighting dependence on feature measurement methods and the need for careful calibration and external validation. This series of investigations identifies two major factors for early-stage risk assessment: (i) models should be evaluated on early-pregnancy attributes; and (ii) reliability (calibration, Brier score) and external validation are prerequisites for clinical use.

E. Machine Learning Models for Predicting Gestational Complications

Tomar *et al.* [8] used machine learning techniques to predict pregnancy complications based on maternal demographic and physiological data. The authors evaluated different classifiers, including decision trees, logistic regression, and support vector machines, and reported improved prediction accuracy compared with traditional statistical approaches. The study demonstrated that supervised learning models could be useful for the early warning of high-risk pregnancies. The paper focused primarily on forecasting isolated complications and did not include ensemble learning or explainability approaches, limiting its scope for comprehensive clinical decision support.

F. Early Pregnancy Risk Assessment Using Data-Driven Approaches

In a related study, Pi *et al.* [9] investigated the relationship between clinical decision-support systems and explainable artificial intelligence methods. The work emphasized transparency, interpretability, and trust as the three main factors contributing to the acceptance of machine learning models in healthcare. The authors discussed, among others, post-hoc explanation approaches such as SHAP and LIME, focusing on their ability to provide a direct link between predictive accuracy and clinical relevance. The review highlighted the promise of explainable AI in maternal healthcare, while also noting limitations, especially in multi-risk prediction scenarios, thereby motivating the current study to address this challenge.

G. Explainable AI for Clinical Decision Support in Healthcare

In another study, Vasudevan *et al.* [10] reviewed various explainable artificial intelligence techniques applied in clinical decision-support systems and explained that transparency, interpretability, and trust are the main factors that need to be addressed before machine learning models can be widely accepted in the medical field. They discussed post-hoc explanation methods such as SHAP and LIME and noted that these methods are effective in reducing the gap between predictive performance and clinical usability. However, the review highlighted that the use of explainable AI in maternal healthcare, especially in multi-risk prediction scenarios, has remained very limited, thereby creating a research gap that the current study aims to address.

III. MATERIALS AND METHODOLOGY

This section outlines the materials, data sources, and methodological approach used in the study to develop an explainable ensemble machine learning model for forecasting complications in high-risk pregnancies during the early trimester. The comprehensive workflow includes dataset selection, data preprocessing, modeling, training, and evaluation. Clinical and demographic factors obtained in the first trimester of pregnancy were used as input features for developing supervised learning models. To increase predictive power and robustness against noise, various base classifiers were combined through an ensemble learning approach. Standard classification metrics were applied to estimate model accuracy and evaluate correct predictions, generalization, and reliability. In addition, explainable artificial intelligence (XAI) was employed to provide both global and local interpretations of the model's predictions.

A. Dataset Description

The study utilizes the Maternal Health Risk Dataset, a publicly available dataset that has gained popularity in pregnancy risk prediction because of its clinical transparency. The dataset consists of 1,014 hospital records reflecting initial clinical assessments of pregnant women, focusing mostly on first-trimester evaluations. It contains six input attributes: maternal age, systolic blood pressure, diastolic blood pressure, blood sugar level, body temperature, and heart rate, all of which are major indicators of pregnancy complications. The target variable is categorical and represents three levels of pregnancy risk—Low Risk, Medium Risk, and High Risk—with 406, 336, and 272 cases, respectively. This class distribution provides representation across the three risk categories minimizes classification bias and supports better model training and evaluation. All features are numeric, which facilitates the application of machine learning methods. The dataset serves as the foundation for developing explainable predictive models for early-trimester pregnancy risk assessment.

B. Data Preprocessing

The Maternal Health Risk Dataset was confirmed to be complete because all documented features were present, so no imputation methods were required. To ensure uniform feature representation and accelerate model convergence, numerical features such as blood pressure, blood glucose level, body temperature, and heart rate were normalized using standard scaling. This procedure was particularly important for distance- and margin-based classifiers such as Support Vector Machines, which are sensitive to differences in feature scales. The pregnancy risk level variable was numerically encoded to facilitate multi-class classification. The dataset was then split into training and testing subsets

using a stratified split method that preserved the original class distribution across risk categories.

C. Model Architecture

The proposed model architecture combines the strengths of various machine learning classifiers through an ensemble learning approach to enable accurate and trustworthy early-trimester multi-risk prediction. The proposed architecture is illustrated in Figure 1. The study uses three widely adopted supervised learning methods—Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM)—as base classifiers. Random Forest was selected for its ability to handle complex relationships and reduce overfitting through an ensemble of decision trees. XGBoost was selected because of its strong performance on structured clinical datasets and its ability to capture complex feature interactions accurately. Support Vector Machine was adopted because of its effectiveness in high-dimensional feature spaces and strong generalization ability. The outputs from these base classifiers were combined using a soft-voting ensemble strategy, whereby the predicted class probabilities for each category were summed to determine the final risk category.

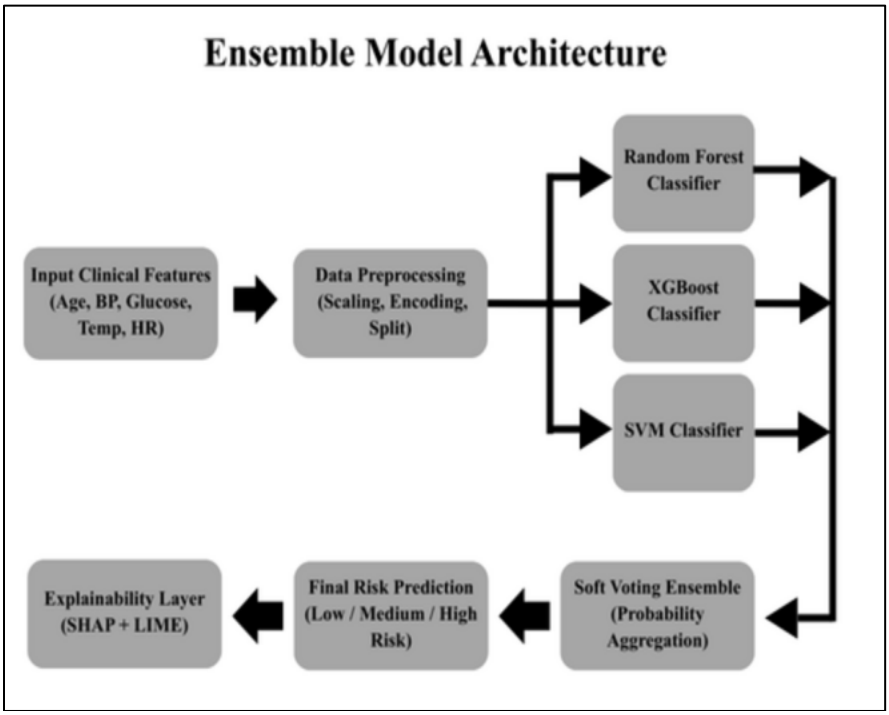


Fig.1 Architecture of the Proposed Explainable Ensemble Learning Framework

D. Training Strategy

The training approach was designed to ensure a consistent learning process, strong generalization, and unbiased evaluation of the proposed ensemble model. Each base classifier in the ensemble—Random Forest, XGBoost, and Support Vector Machine—was trained separately on the preprocessed training dataset. Standard and widely recognized hyperparameter settings were applied initially, followed by empirical adjustments to maintain consistent performance across all risk categories. Stratified sampling was used in the train-test split to preserve class distribution and avoid bias toward larger classes. Model performance was evaluated using multi-class classification metrics, including accuracy, precision, recall, and F1-score. In addition, receiver operating characteristic (ROC) analysis and area under the curve (AUC) were used to evaluate the model's ability to distinguish among different risk categories. To further strengthen confidence in the proposed framework, k-fold cross-validation was implemented during training, enabling validation on different subsets of the data.

E. Explainability Methods (SHAP and LIME)

Explainability is important in medical decision-support systems because clinicians need to understand how a model arrives at its predictions before using them. The proposed ensemble learning framework was equipped with Explainable Artificial Intelligence (XAI) methods that provided global and local explanations of model predictions. SHAP was used to investigate the global behavior of the trained models by examining how each input feature contributed to prediction results. In this work, SHAP was applied to the ensemble's tree-based components to identify important clinical variables across different pregnancy risk categories. Global SHAP summary plots were produced to visualize feature importance and understand how changes in feature values influence predicted risk levels. To complement global explainability, Local Interpretable Model-agnostic Explanations (LIME) were applied to provide instance-based explanations for individual predictions. At the local level, LIME approximates the complex ensemble model with a

simpler surrogate model, making it possible to explain specific predictions in terms of feature contributions.

IV. RESULTS

This section presents the experimental results obtained from the proposed explainable ensemble learning framework for early-trimester multi-risk prediction of pregnancy complications. The performance of individual baseline models and the ensemble model was evaluated using multi-class classification metrics. In addition, robustness was assessed through cross-validation, and discriminative ability was examined using ROC-AUC analysis and calibration curves.

A. Model Performance Evaluation

The predictive performance of the baseline Random Forest classifier and the proposed soft-voting ensemble model is summarized in Table I. The ensemble model achieved higher performance than the individual baseline model across all evaluation metrics. Specifically, the ensemble model attained an accuracy of 88% and a macro F1-score of 0.89, indicating improved classification performance across the three pregnancy risk categories.

TABLE I PERFORMANCE COMPARISON OF BASELINE AND ENSEMBLE MODELS

Model	Accuracy	Precision (macro)	Recall (macro)	F1-score (macro)
Random Forest	0.86	0.87	0.87	0.87
Ensemble (RF + XGBoost + SVM)	0.88	0.89	0.89	0.89

B. Confusion Matrix Analysis

The confusion matrix provides a comprehensive analysis of the ensemble model's classification effectiveness across the three pregnancy risk categories: Low Risk, Medium Risk, and High Risk.

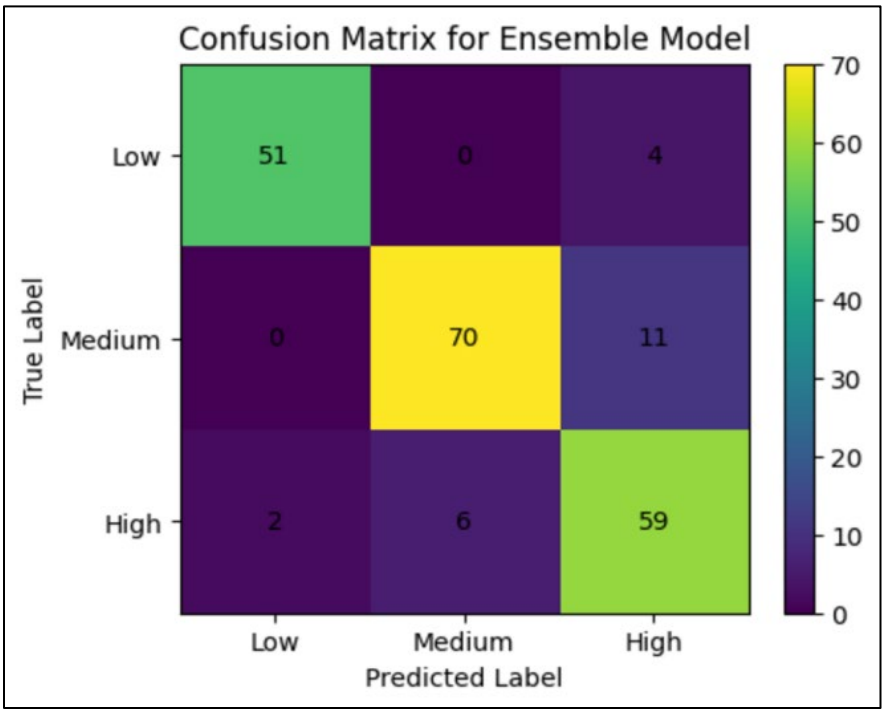


Fig.2 Confusion Matrix of the Ensemble Model

As shown in Figure 2, most instances in every class were accurately classified, reflecting successful learning of class-specific patterns from early-trimester clinical features. The model exhibited robust performance in recognizing Low Risk and High Risk cases, with only a few instances incorrectly categorized into neighboring risk categories. Misclassifications mainly occurred between Medium Risk and adjacent categories, which is anticipated because of shared physiological traits among borderline instances.

C. ROC-AUC Analysis

The performance of the proposed ensemble model was further verified using multi-class receiver operating characteristic (ROC) analysis. The ROC-AUC measure

indicates the model's ability to distinguish among different pregnancy risk levels at various classification thresholds. The ensemble model achieved a macro-average ROC-AUC of 0.967, as shown in Figure 3, reflecting excellent overall discrimination. Class-wise evaluation revealed AUC values of 0.990 for Low Risk, 0.956 for Medium Risk, and 0.953 for High Risk groups.

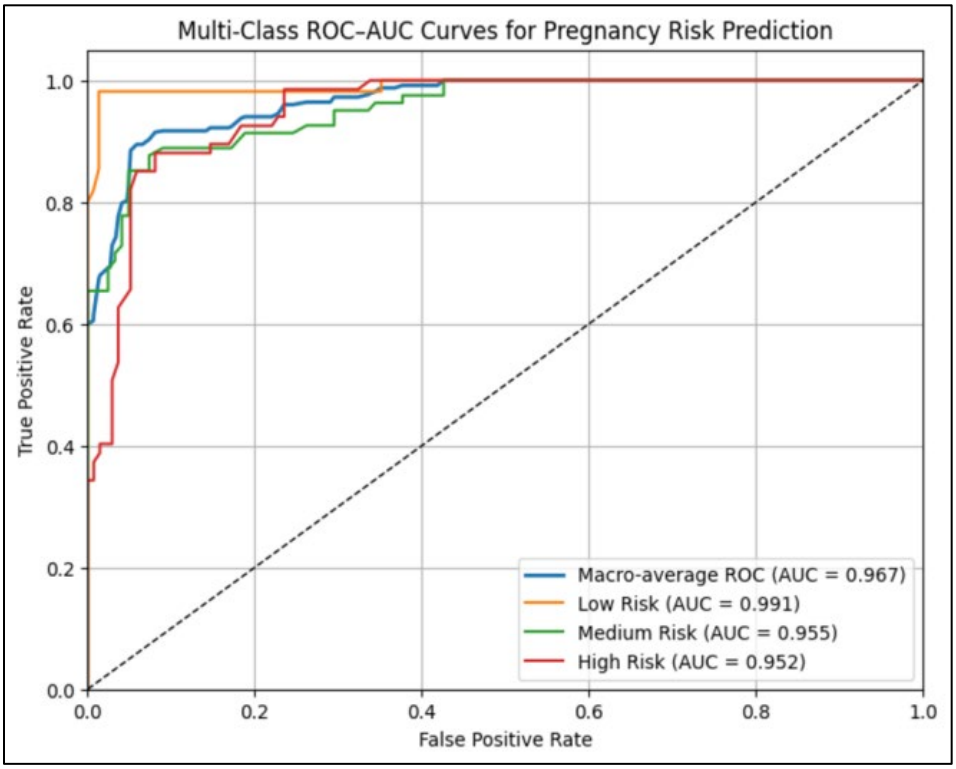


Fig.3 Multi-class ROC-AUC Curves for the Ensemble Model

D. Cross-Validation Results

To assess model stability and generalization, k-fold cross-validation was conducted on the ensemble model. The cross-validation results are presented in Table II. The ensemble model reached a mean macro F1-score of 0.868 with a standard deviation of 0.022, demonstrating reliable performance across several data divisions.

TABLE II CROSS-VALIDATION PERFORMANCE OF THE ENSEMBLE MODEL

Metric	Value
Mean macro F1-score	0.868
Standard deviation	0.022

E. Calibration Analysis

Calibration performance was assessed using calibration curves and Brier scores to evaluate the reliability of predicted probabilities. The ensemble model demonstrated well-calibrated probability estimates across all risk categories. The calibration curves illustrated in Figure 4 demonstrate strong alignment between predicted and observed risk probabilities across all pregnancy risk categories. The Brier scores obtained were 0.025 for Low Risk, 0.086 for Medium Risk, and 0.091 for High Risk classes.

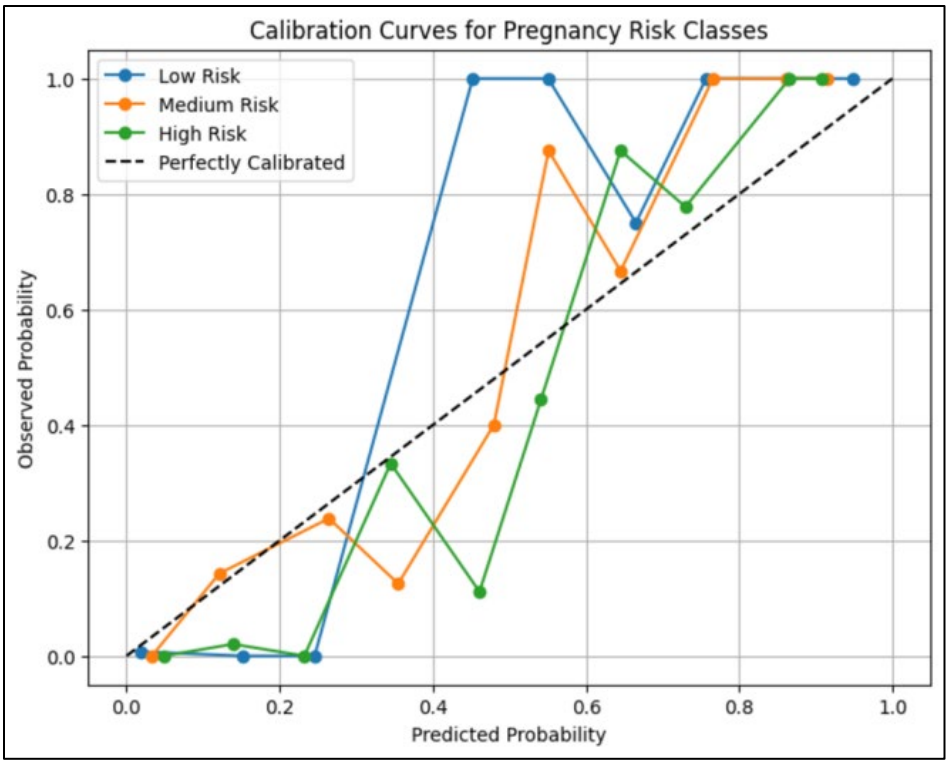


Fig.4 Calibration Curves of the Ensemble Model

V. DISCUSSION

The experimental results showed that the proposed explainable ensemble learning framework can predict multiple risks of pregnancy complications during the early trimester. The ensemble model consistently outperformed the individual baseline classifier across all evaluation metrics, achieving higher accuracy, macro precision, recall, and F1-score. This improvement highlights the integration of different base learners as a major advantage because the ensemble method reduces the biases of individual models while capturing diverse patterns in early-pregnancy clinical data. Confusion matrix analysis showed balanced classification across the Low Risk, Medium Risk, and High Risk categories, with most misclassifications occurring between adjacent risk levels. This behavior is expected in medical datasets, where physiological measurements often overlap in borderline cases. The model showed almost no confusion between the extreme risk categories, confirming a clear distinction between low-risk and high-risk pregnancies. The strong multi-class ROC-AUC values further confirm the model's ability to distinguish among different risk categories, even when using limited early-trimester features.

A. Explainability Analysis and Clinical Insights

Explainability analysis using SHAP and LIME provided valuable insights into the decision-making process of the ensemble model. Global SHAP analysis revealed that maternal blood pressure, blood glucose levels, age, and heart rate are key factors influencing pregnancy risk prediction. The global SHAP summary plot is shown in Figure. 5. These results have clinical significance because high blood pressure and glucose levels are recognized indicators of hypertensive conditions and gestational diabetes, respectively.

Local explainability through LIME improved transparency by detailing individual patient predictions. Instance-level explanations enable clinicians to understand why a specific patient was assigned to a particular risk category, facilitating individualized risk evaluation. LIME explanations are shown in Figure.6. The addition of SHAP interaction plots showed that pairs of clinical features collectively affect risk predictions, illustrating the model's ability to recognize complex nonlinear relationships rather than depending solely on individual features.

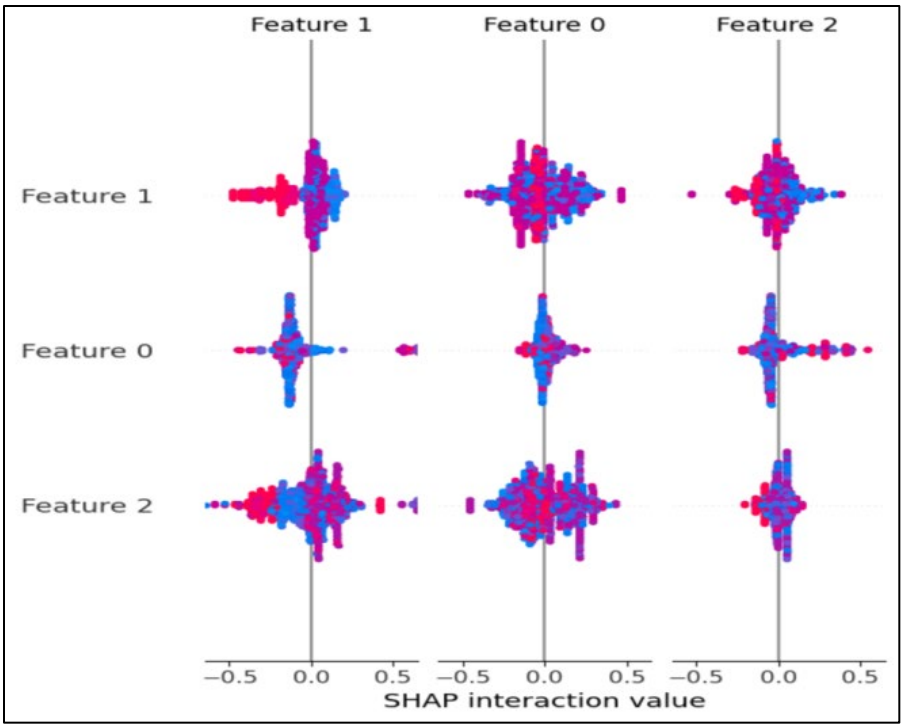


Fig.5 SHAP Summary Plot Illustrating the Global Importance of Clinical Features Contributing to Early-Trimester Pregnancy Risk Prediction

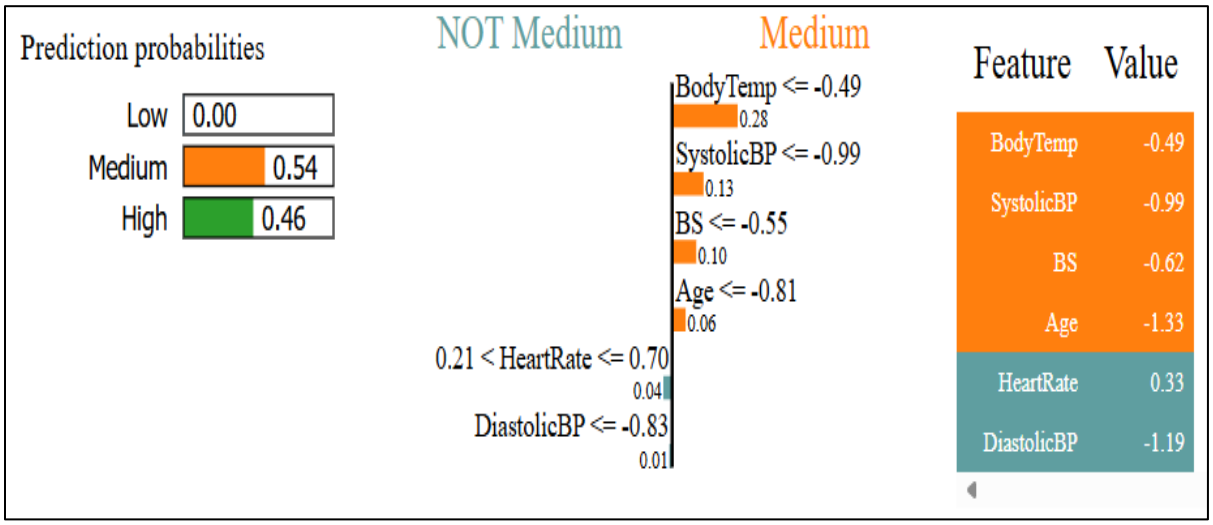


Fig.6 LIME Explanation for an Individual Patient, Highlighting Feature Contributions Toward the Predicted Pregnancy Risk Class

B. Comparison with Previous Studies

The findings of this research confirm the results of previous studies that highlighted the greater accuracy of ensemble learning approaches for forecasting maternal health risks. Past studies have shown that ensemble methods outperform individual classifiers in both accuracy and stability. However, most previous research has focused on single-risk prediction or later pregnancy stages. In contrast, the current research focuses on multi-risk prediction in the early trimester, enabling timely intervention. Previous studies have used explainable AI techniques, but the current research extends the existing body of knowledge by incorporating explainability within an ensemble framework and evaluating both global and local interpretations. Unlike previous approaches that relied on SHAP or LIME separately, the proposed framework combines performance improvement, explainability, and calibration assessment in a single pipeline.

C. Limitations

This study has some limitations despite the promising results. Initially, the research was conducted using only one public dataset, which could limit the transferability of the findings to different populations and medical facilities. In addition, although the dataset size was sufficient for evaluating machine learning, it remains relatively small compared with large clinical datasets. Only structured clinical and demographic data were analyzed, while longitudinal data and imaging information were excluded.

VI. CONCLUSION

The paper discusses the development of an explainable ensemble machine learning model for multi-risk forecasting of early pregnancy complications in the first trimester using clinical and demographic data. The proposed technique integrates Random Forest, XGBoost, and Support Vector Machine classifiers through a soft-voting ensemble strategy, resulting in improved predictive performance and reliability. The experimental results show that the ensemble model achieves strong classification performance across three categories—Low Risk, Medium Risk, and High Risk—as indicated by its higher accuracy and macro F1-score than the individual baseline models. High multi-class ROC-AUC scores and favorable calibration results indicate that the model provides reliable separation and well-calibrated probability predictions, which are important for risk-sensitive clinical practice. Confusion matrix analysis supports balanced performance across all risk categories, with very few errors between adjacent risk levels. A major contribution of this research is the combination of explainable AI methods with the ensemble structure.

VII. FUTURE SCOPE

The proposed explainable ensemble learning framework provides a firm foundation for early-trimester pregnancy risk prediction. However, several opportunities are available for its improvement and eventual clinical implementation. One future research direction is to validate the framework using large, diverse datasets obtained from different healthcare facilities, which would support broader application across different populations and clinical settings. Another direction is to use longitudinal and temporal data throughout pregnancy for continuous risk assessment and early detection of complications. Additional clinical data, such as laboratory results, imaging findings, and lifestyle factors, may also be incorporated to improve predictive accuracy and risk stratification. Moreover, advanced deep learning models and federated learning approaches could be explored to utilize distributed data while preserving patient privacy. Future studies may focus on real-time model implementation in clinical decision-support systems and prospective evaluation in hospital settings.

Declaration of Conflicting Interests
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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
The author(s) utilised generative AI technologies solely to improve language clarity and refine grammar. No images were generated, manipulated, or altered using AI-assisted technologies.

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