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Hybrid Multi-Method Explainable AI and Machine Learning for Early Prediction of High-Risk Pregnancies

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***Abstract* – High-risk pregnancies are the main reason for high maternal and infant mortality and morbidity rates. Efforts to detect these pregnancies early are essential to ensure timely and targeted medical interventions. The objective of this study is to develop a pregnancy risk prediction model that combines machine learning algorithms with a multi-method explainable artificial intelligence approach. Data was collected from five community health center in Koto Tangah District and then pre-processed with steps including cleaning, normalizing, and balancing the classes using the Synthetic Minority Over-sampling Technique method. Four algorithms were tested: Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest. The experimental results showed that the Random Forest and Decision Tree algorithms achieved the highest accuracy, at 88% and 88%, respectively, while the Logistic Regression algorithm had the lowest accuracy, at 63%. Shapley Additive exPlanations, Local Interpretable Model-agnostic Explanations, and Permutation Feature Importance analyses confirmed systolic blood pressure, blood sugar, and diastolic blood pressure as the most influential features. Integrating Multi-Method Explainable Artificial Intelligence produced an accurate, transparent, and relevant model for supporting the early detection and prevention of maternal complication.**

***Keywords* – High risk pregnancies, machine learning, multi-method XAI, maternal, Padang City.**

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1. Introduction

A high-risk pregnancy is one that is influenced by factors that increase the risk of serious health complications for the mother and fetus during pregnancy, childbirth, or the postpartum period. These pregnancies require special attention and treatment to prevent fatal consequences [1], [2], [3], [4]. According to the WHO, approximately 800 pregnant women died each day in 2020 due to preventable pregnancy and childbirth complications. Twenty to thirty percent of pregnancies are classified as high-risk, accounting for seventy to eighty percent of perinatal deaths and morbidity [5], [6], [7], [8]. Maternal deaths are usually caused by complications like severe bleeding, pregnancy-induced hypertension, infections, unsafe abortions, and chronic diseases that worsen during pregnancy [9], [10], [11]. A variety of factors can contribute to an elevated risk, including medical history, advanced age, poor lifestyle habits, socioeconomic background, and ongoing pregnancy complications [12], [13], [14]. The potential for complications during pregnancy necessitates preventive solutions to protect both mothers and Fetuses [15], [16], [17], [18]. Pregnancy is a biological process that requires special attention to ensure the health of both the mother and the Fetus [19], [20], [21].

Pregnancy risks are dynamic. A mother's initially normal condition can suddenly become high-risk [22], [23]. High-risk pregnancies can be prevented through early detection of complications and routine checkups during pregnancy [24]. The detection of high-risk pregnancies is an effort by health workers to identify pregnant women, women in Labor, and women in the postpartum period who are at risk for complications and ensure their safety.

Machine learning algorithms can predict high-risk pregnancies [25], [26], [27], [28], [29]. The goal is to improve maternal and fetal safety, overcome the limitations of manual diagnosis, reduce maternal and infant mortality rates, improve healthcare efficiency, and support digital healthcare systems and artificial intelligence in medicine in the Koto Tangah subdistrict [30].

Literature review: The research is titled "Prediction of Maternal Health Risk Factors Using Machine Learning Algorithms". This study uses real data from a rural IoT system, making it relevant to real-world conditions. Of the various algorithms compared, Ensemble Bagged Trees demonstrated the highest accuracy (84.12%) and high recall. Evaluating the results using precision, recall, the F1-score, the ROC curve, and Explainable AI-PFI makes them more interpretable and applicable to the early detection of maternal risks [31]. Another study is titled "Ensemble Machine Learning Framework for Predicting Maternal Health Risk During Pregnancy." The study presents advantages through the Quad-Ensemble Machine Learning (QEML-MHRC) framework, which combines various algorithms with ensemble techniques. This approach effectively addresses multiclass classification and data imbalance, achieving 90% accuracy in the high-risk class. Using precision, recall, and F1-score to evaluate the results enhances their reliability for the early detection of maternal health risks [32].

2. Method

This study uses a machine learning approach to create a reliable, easy-to-understand prediction model [33], [34], [35], [36], [37]. The process begins with collecting and cleaning data to ensure quality and balance. Various algorithms' performance, such as Logistic Regression [38], Decision Tree [39], Support Vector Machine [40], Random Forest [41], [42], was compared with the others. The evaluation was conducted using metrics such as accuracy [43], precision [44], recall [45], F1- score, and AUC-ROC [46]. After obtaining the optimal model, it is interpreted using multiple explainable artificial intelligence methods (XAI) [47], [48], namely Shapley additive explanations (SHAP) [49], Local Interpretable Model-Agnostic Explanations (LIME) [50] and Permutation Feature Importance (PFI) [51]. The goal is to identify the contribution of each feature to the prediction. This approach aims to produce an accurate and transparent model to support the decision-making process [52], [53]. The architecture of the multi-method Explainable AI-based machine learning model process can be seen in Figure 1.

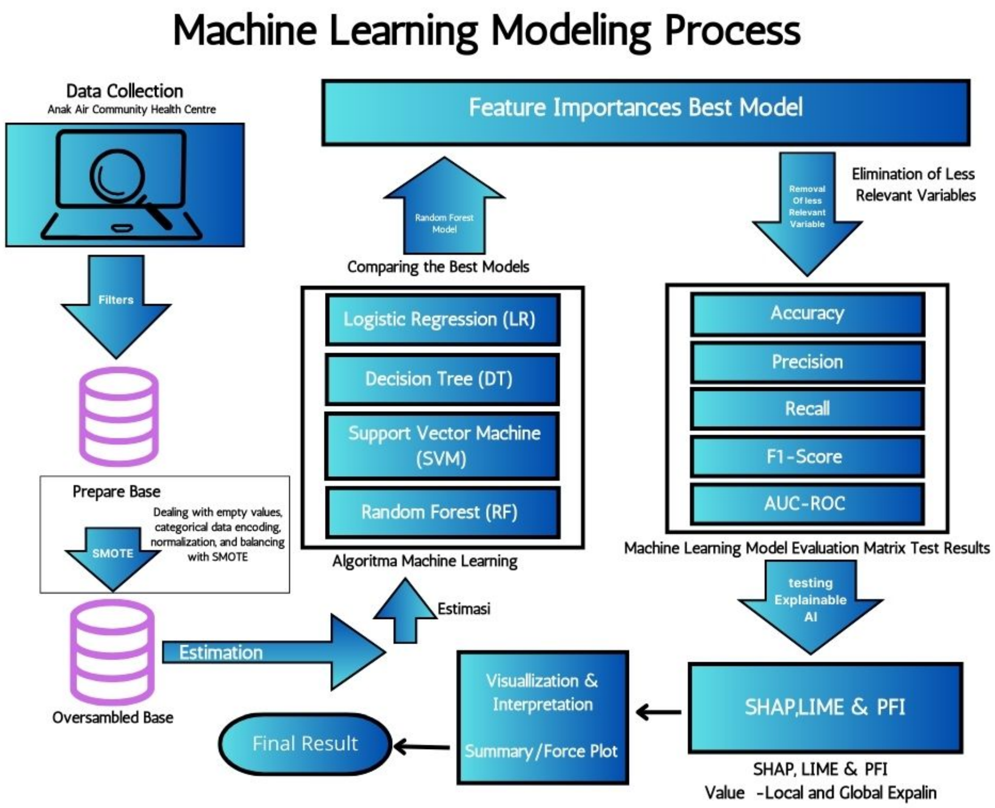


Figure 1. Multi-method Explainable AI-based machine learning modeling process

The goal of this study is to design a robust machine learning model for analyzing public health data from five community health centers in Koto Tangah District. Model development is carried out through several stages:

a. Data Collection Process: The first step was to collect data from five community health center. This data was then filtered to ensure that only relevant features were used in the analysis.

b. Preprocessing Data: The data was cleaned and processed. This included handling missing data, transforming categorical variables, normalizing, and balancing classes. The SMOTE (Synthetic Minority Over-sampling Technique) method was used to produce a balanced, train-ready dataset [54], [55], [56], [57], [58].
c. Modeling with Machine Learning Algorithm: Several machine learning algorithms were tested, including Logistic Regression, Decision Tree, SVM, and Random Forest, to compare their predictive capabilities [40], [59], [60], [61], [62]. Testing models using the Python programming language [63], [64].
d. Model Performance Evaluation: model performance was analyzed using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Based on the evaluation results, the best model was selected, and important features were analyzed to improve model efficiency [65], [66].
e. Interpretability of Classification Model: The best-performing models were analyzed using multi-method XAI techniques, including SHAP, LIME, and PFI. The goal was to measure and visualize how each feature contributes to the prediction, both overall and individually, so users and stakeholders could understand the results [67].

3. Results

This section presents the results of the evaluation of several machine learning models' performance in predicting preeclampsia risk. It also discusses the contribution of each feature based on the Multi-Method XAI approach using SHAP, LIME, and PFI.

3.1. Pre-Processing Data

Data pre-processing constitutes a fundamental component in ensuring data quality and validity prior to its use in machine learning model training. The dataset analyzed in this study consists of 1,462 clinical records of pregnant women collected from five community health centers in Koto Tangah District, Padang City, thereby representing primary-level healthcare services. The predictor variables include clinical attributes obtained through routine examinations, namely age, systolic blood pressure, diastolic blood pressure, blood glucose level, body temperature, and heart rate. The target variable was defined as the level of pregnancy risk, classified into three categories: low risk, mid risk, and high risk. The clinical and demographic features of the pregnant women dataset are summarized in Table 1.

Table 1. Clinical and demographic features in the pregnant women dataset

	Age	Systolic Bp	Diastolic BP	BS	Body Temp	Heart Rate	Risk level
0	29	130	70	7.7	98.0	78	Mid risk
1	30	140	100	15	98.0	70	High risk
2	40	140	95	17	98.0	60	High risk
3	23	120	90	7.5	98.0	60	Low risk
4	17	120	80	7.5	102.0	76	Low risk

The first step was to verify that the data were complete. The results showed that all data entries were complete, so handling missing values was not necessary. Next, the data were explored using boxplots and histograms to identify outliers and distribution patterns. Standardization using z-scores was performed for numerical features, especially for models sensitive to data scales, such as SVM.

The category labels in the Risk Level column are recoded as follows: low risk = 0, medium risk = 1, and high risk = 2. Then, the dataset is divided into training and testing data with an 80:20 ratio using stratified sampling to maintain proportional class distribution. All of these steps are performed using the Python library.

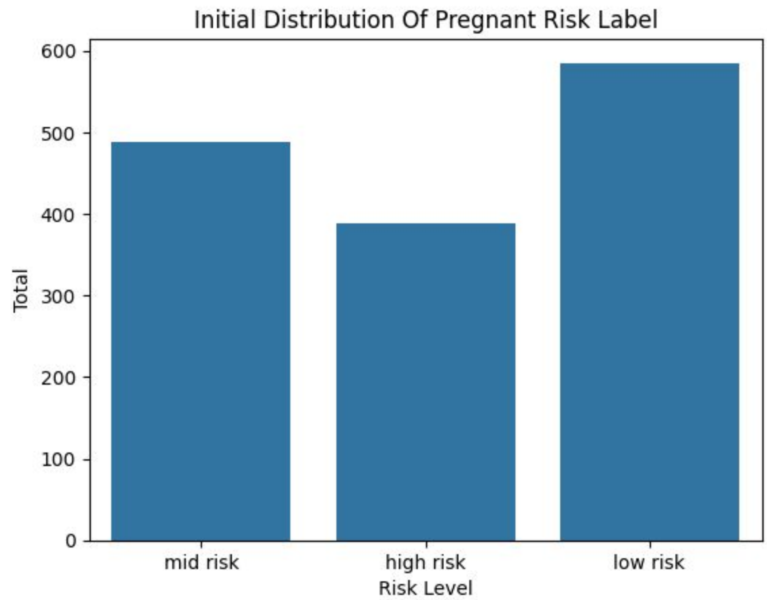


Figure 2. Distribution of pregnancy risk labels before data process

Figure 2 illustrates the initial distribution of pregnancy risk level labels in the dataset. The low-risk category has the most data points (585), followed by the mid-risk category (488), and finally the high-risk category (388). This distribution indicates that the low-risk group accounts for approximately 40% of the total data, while the mid- and high-risk groups represent approximately 33% and 27%, respectively.

3.2. Distribution of Pregnancy Risk Classes After SMOTE Oversampling

The distribution shows class imbalance, which affects model performance, especially at high risk. To make predictions more balanced and accurate, the solution is to use stratified sampling, oversampling, or minority class weighting.

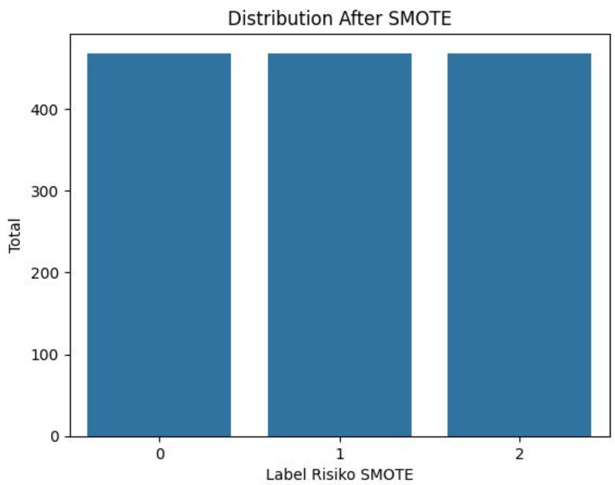


Figure 3. Distribution of pregnancy risk classes after SMOTE oversampling

Figure 3 illustrates the distribution of pregnancy risk labels after data balancing with the SMOTE method. After applying this process, each of the three risk labels 0 for low risk, 1 for middle risk, and 2 for high risk had an equal number of samples 468 each.

3.3. Confusion Matrix of Pregnancy Risk Prediction

A confusion matrix evaluates the performance of a classification model by showing the number of correct and incorrect predictions in each category. This facilitates analysis of the model's accuracy and classification error.

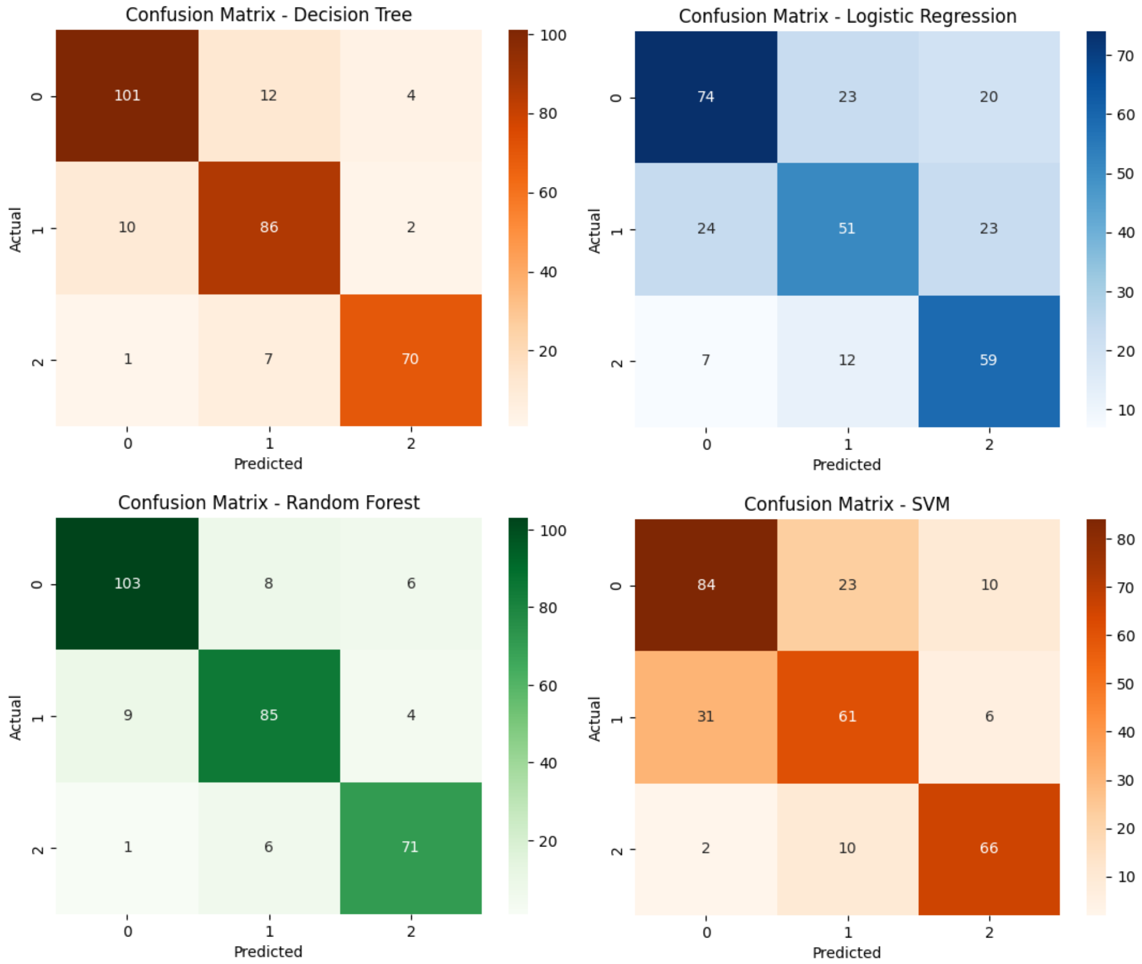


Figure 4. Confusion Matrix of pregnancy risk prediction

The results of the confusion matrix analysis demonstrate the differences in performance among the classification models (Figure 4). Random Forest performed the best, successfully classifying 103 class 0 data, 85 class 1 data, and 71 class 2 data correctly. The Decision Tree model also produced satisfactory results, correctly predicting 101, 86, and 70 instances. SVM is intermediate, performing poorly in class 1 (61/98 correct).

Logistic regression shows the lowest performance, with many errors, particularly in classes 1 and 2. Performance order: Random Forest > Decision Tree > SVM > Logistic Regression. Table 2 presents comparison of pregnancy risk classification model.

Table 2. Comparison of pregnancy risk classification model performance

Model	Accuracy	Macro Avg (F1)	Brief comments
Random Forest	0.88	0.88	Best accuracy and stability.
Decision Tree	0.88	0.88	It is excellent and reliable.
SVM	0.72	0.73	There is enough stronger performance.
Logistic Regression	0.63	0.63	Lowest performance, especially for mid risk.

3.4. Roc Curve

The ROC curve evaluates a model's ability to distinguish between classes.

It displays the relationship between the true positive rate and the false positive rate. It also measures performance through the area under the curve (AUC) value.

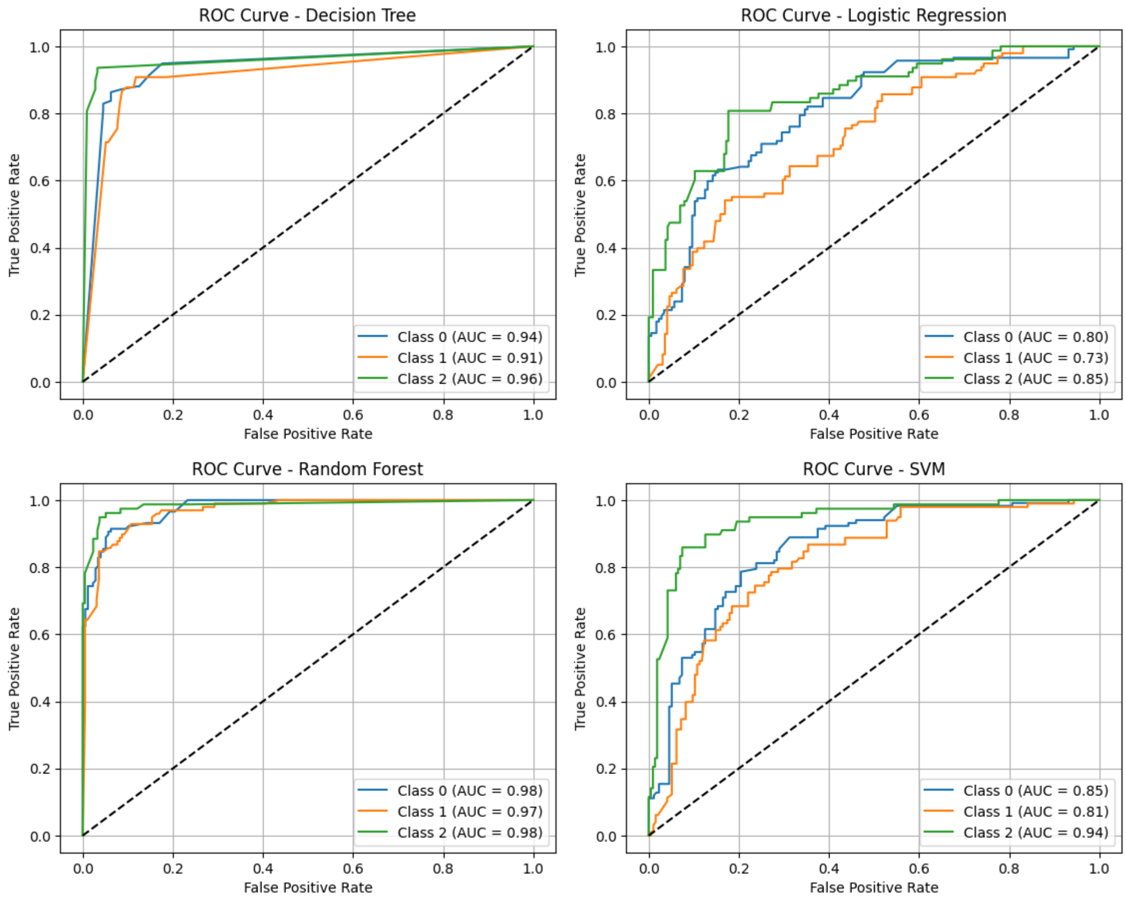


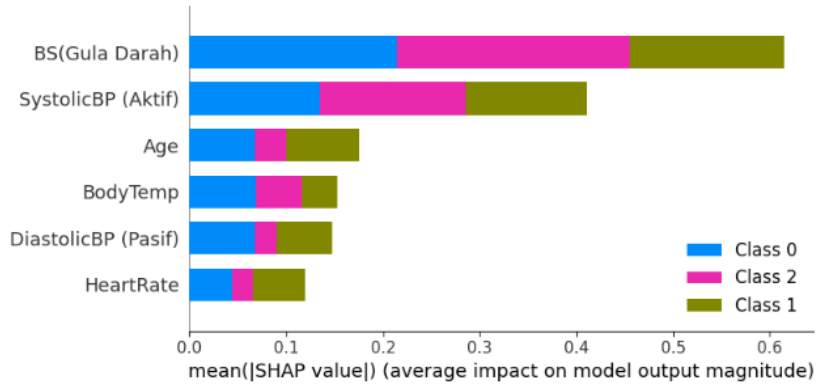
Figure 5. Classification Model Performance based on ROC curve

The Random Forest model demonstrated optimal performance, achieving an AUC value close to perfection across all classes and confirming its effectiveness in risk classification (Figure 5). The Decision Tree also provided good results, though slightly below those of the Random Forest. The SVM model performed moderately well, showing strength in high-risk classes but weakness in others. Logistic Regression showed the lowest performance, especially in class 1, with a low AUC.

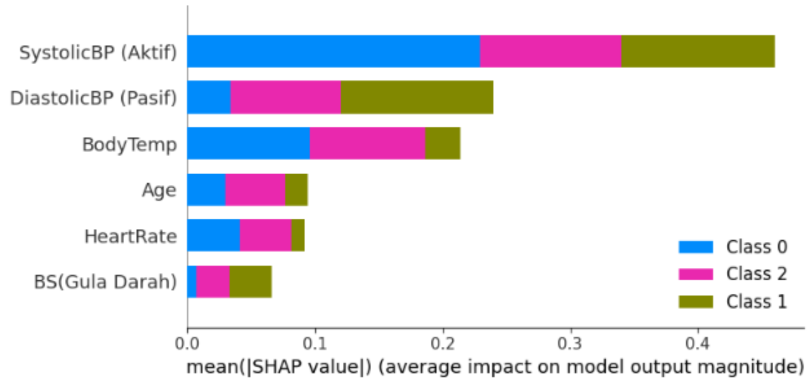
Overall, the order of performance is as follows: Random Forest, Decision Tree, SVM, and Logistic Regression.

3.5. Model Interpretability Through SHAP Visualization

SHAP is used to explain how each feature contributes to a model's prediction. It provides a transparent, in-depth interpretation of the decisions made by a machine learning algorithm.



a)



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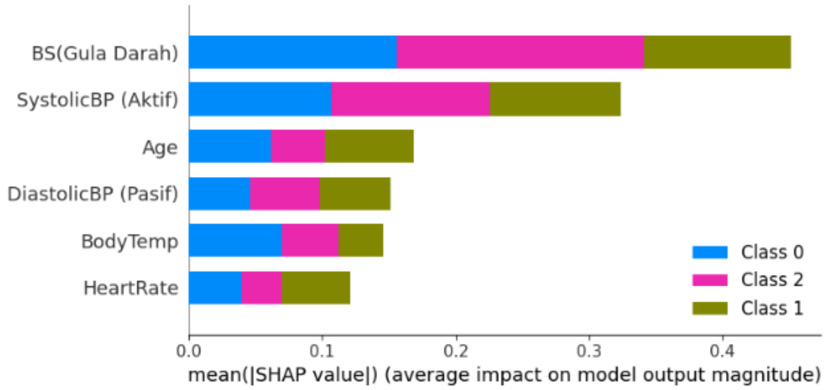

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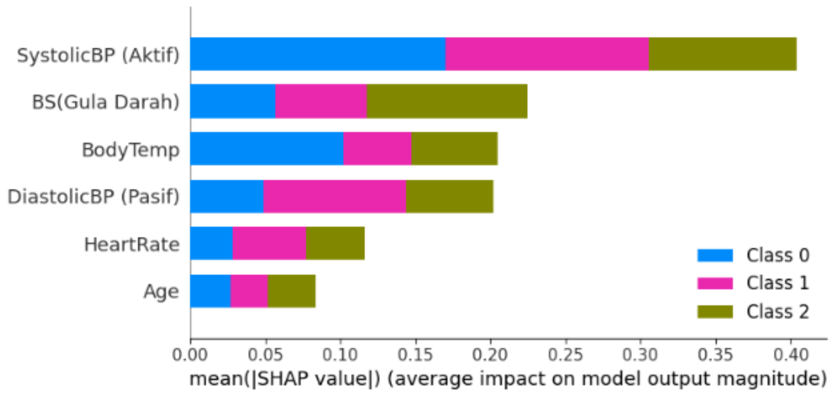

d)

Figure 6. Model Interpretability through SHAP Visualization; a) Shap Decision Tree, b) Shap Logistic Regression, c) Shap Random Forest, d) Shap Support Vector Machine

This SHAP visualization shows how the four algorithms vary in their contributions to predicting high-risk pregnancies (Figure 6).

The Decision Tree emphasizes blood sugar and systolic blood pressure, Systolic BP, Logistic Regression dominates Systolic BP, Random Forest is more balanced but still highlights both, and SVM is evenly distributed across several features. Systolic BP and blood sugar consistently emerge as important indicator.

3.6. Model Prediction Visualization Through LIME.

LIME is used to explain how features contribute to local model predictions, which facilitates interpretation of complex decisions and reveals differences in focus between algorithms for each risk category.

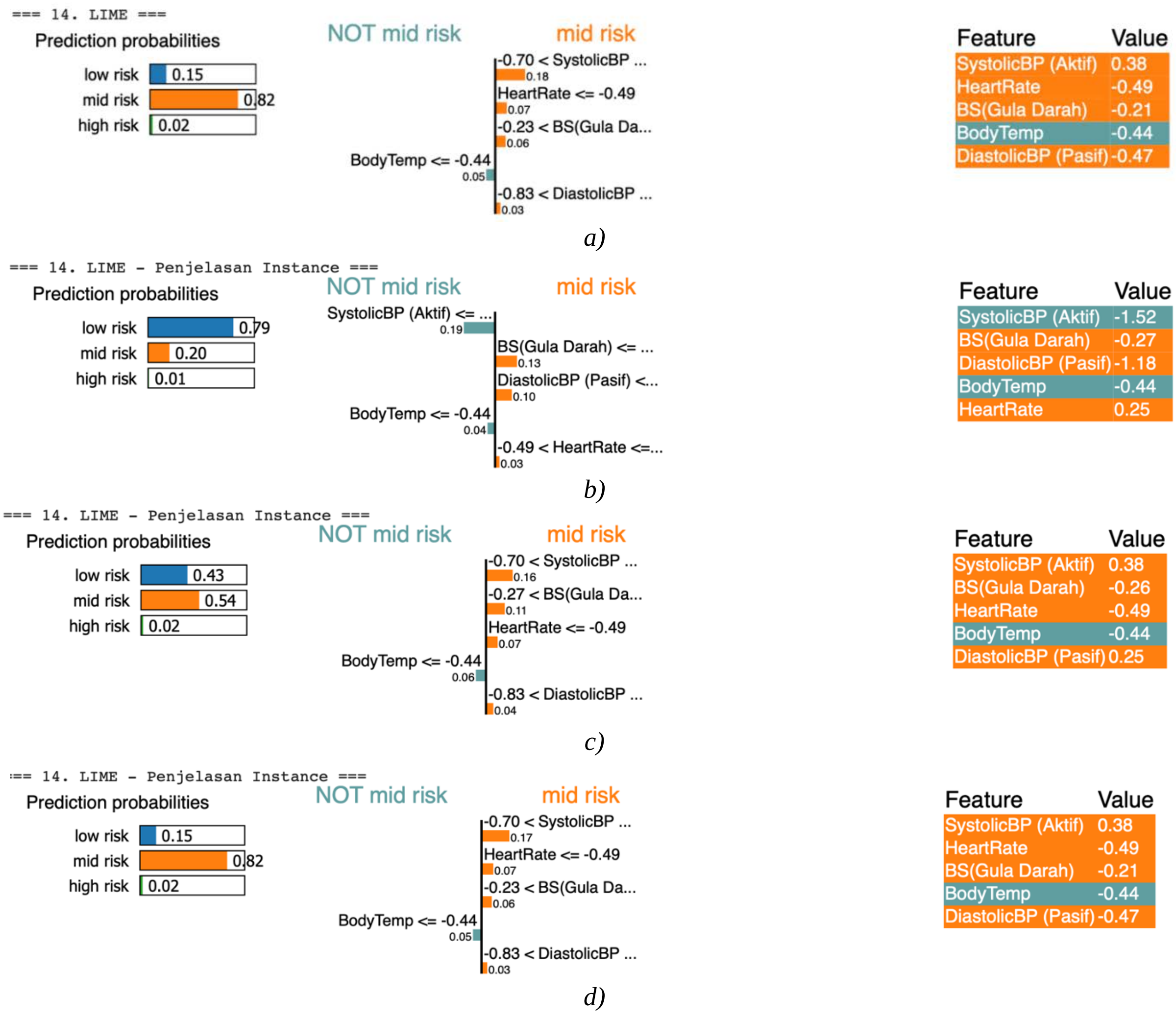

Figure 7. Model Prediction visualization through LIME
a)Support Vector Machine, b) Random Forest, c) Logistic Regression, d) Decision Tree

LIME interpretation shows that all models identify Systolic BP as the most influential factor, followed by blood sugar and heart rate (Figure 7). SVM and decision tree models predominantly predict the mid-risk category, while random forest models tend more toward low risk. Logistic regression shows a balance between low- and mid-risk predictions. These findings emphasize that systolic blood pressure is the most consistent factor in determining risk level.

3.7. Model Interpretation Using Permutation Feature Importance (PFI)

This section provides PFI visualizations that assess how each feature contributes to model performance. A feature's importance is determined by how much its randomized value decreases the model's accuracy. The largest decrease indicates the most significant influence on risk prediction.

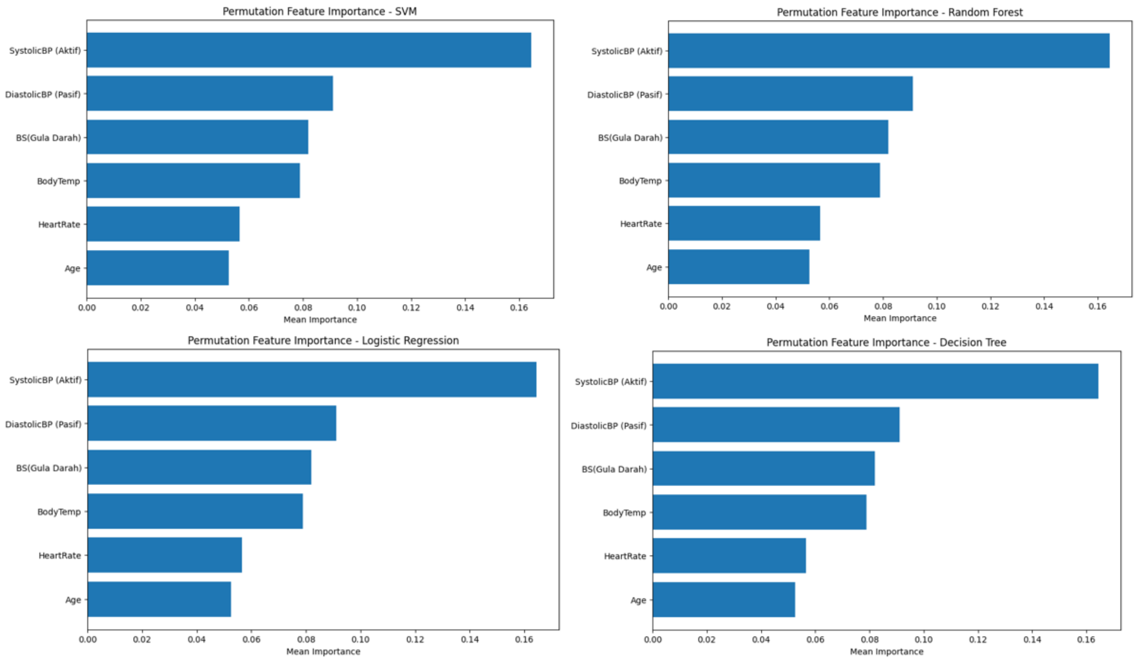

Figure 8. Model Interpretation using Permutation Feature Importance (PFI)

The four models (SVM, Random Forest, Logistic Regression, and Decision Tree) show similar trends. Systolic BP emerges as the most influential feature, followed by diastolic BP and blood sugar (Figure 8). Meanwhile, body temperature, heart rate, and age contribute relatively little. These results confirm that blood pressure and blood sugar levels play dominant roles in influencing predictions in all used algorithms.

4. Discussion

This study confirms that machine learning models based on decision trees specifically, Random Forest and Decision Tree - are effective in predicting high-risk pregnancies with 88% accuracy. These results align with those of previous studies. For instance, one study reported that ensemble bagged trees achieved 84.12% accuracy with high recall on rural IoT data. Another study successfully achieved 90% accuracy in the high-risk category using the quad ensemble machine learning approach. These consistent findings confirm that ensemble approaches based on trees outperform linear models when handling complex maternal data.

The interpretability analysis in this study used Multi-Method XAI methods, such as SHAP, LIME, and PFI. This analysis is consistent with previous literature emphasizing systolic blood pressure, blood sugar, and diastolic blood pressure as main determinants of pregnancy complication risk. These findings further strengthen the clinical relevance of the model and confirm that integrating Multi-Method XAI provides the transparency necessary for supporting medical decision-making.

5. Conclusion

This study demonstrates that machine learning algorithms integrated with multi-method explainable AI (XAI) techniques can provide accurate and interpretable predictions for high-risk pregnancies. Test results indicate that Random Forest achieved the highest accuracy (88%), followed by Decision Tree (88%), while Logistic Regression showed the lowest performance (63%). Feature importance analysis using SHAP, LIME, and PFI identified systolic blood pressure and blood sugar as the most influential predictors, supported by diastolic blood pressure, whereas other variables contributed to a lesser extent. The integration of interpretability methods enhances not only predictive performance but also transparency, thereby supporting more informed clinical decision-making.

From a practical perspective, the proposed framework may be further developed into a clinical decision support system for primary healthcare settings, particularly in regions with limited access to medical specialists. Nevertheless, this study has several limitations, including a relatively small dataset, data coverage restricted to a single region, and the absence of additional relevant variables such as nutritional status, lifestyle factors, and family medical history. Future research should incorporate larger and more diverse datasets with more comprehensive clinical and sociodemographic indicators, to improve model generalizability and robustness. Overall, the findings highlight the potential of integrating machine learning with multi-method XAI approaches to enhance maternal healthcare services through early identification of high-risk pregnancies, thereby contributing to the reduction of complication rates and improvement of pregnancy outcomes.

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