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A RANDOM FOREST ALGORITHM FOR HIGH-RISK PREGNANCIES PREDICTION BASED ON EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

GUSRINO YANTO*, SARI PUSPITA

Department of Information System, Universitas Metamedia, Padang 25133, Indonesia

Abstract: This study explores using the Random Forest (RF) algorithm with the Explainable Artificial Intelligence (XAI) approach to predict High risk in pregnant women. Preeclampsia is a disorder that occurs during pregnancy and is characterized by hypertension and organ damage. If not treated early, it can endanger both the mother and fetus. The RF algorithm was chosen because it can process complex data, resist overfitting, and achieve good classification performance. This study used 299 data points from pregnant women at the Community Health Centre Anak Air in Padang City. The SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) methods were then applied to determine the role of each feature in the prediction process. The results of the analysis show that the RF model effectively identifies pregnancy risk factors, particularly preeclampsia, such as age, body temperature, diastolic blood pressure (BP), blood sugar (BS), heart rate, and urine protein. The model achieved an accuracy of 78%, meaning that 78% of its predictions align with the actual data. The model was interpreted using SHAP and LIME. SHAP reveals globally important features, while LIME provides local explanations based on individual patient characteristics. Users, especially healthcare professionals, can more clearly and informatively understand the prediction results. This approach improves system accuracy and promotes clinical acceptance of AI-based predictive technology. The system can support the early detection of preeclampsia and more accurate decision-making in maternal healthcare.

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*Corresponding author

E-mail address: gusrino@metamedia.ac.id

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1. INTRODUCTION

Preeclampsia is a hypertensive disorder that occurs during pregnancy. It affects approximately 5-8% of high-risk pregnancies and is one of the leading causes of maternal and perinatal morbidity and mortality worldwide [1]. Preeclampsia is a hypertensive disorder that occurs specifically during pregnancy. It usually develops after 20 weeks of gestation and is characterized by high blood pressure, often accompanied by proteinuria or signs of other organ damage [2], [3],[4]. If left undetected or untreated, preeclampsia can progress to eclampsia. Eclampsia is a more severe condition characterized by seizures, which can lead to fatal complications for the mother and fetus [5], [6]. The high rates of maternal and infant mortality due to preeclampsia highlight the need for an early detection system that is both more accurate and efficient. Currently, identifying preeclampsia risk requires manual clinical and laboratory examinations, which are time-consuming and resource-intensive [7]. Additionally, the numerous interrelated risk factors—including maternal age, history of hypertension, previous pregnancies, body mass index, and genetic conditions—make the diagnostic process more complex [8],[4].

A previous study titled "A Machine Learning Model to Predict Preeclampsia in Pregnant Women" introduced an explainable artificial intelligence (XAI)-based framework that uses ensemble learning methods to predict pregnancy complications, particularly preeclampsia. This research primarily aims to improve prediction accuracy while providing explanations understandable to healthcare professionals. This study is an important first step in the local context because the data used came from the medical records of pregnant women in South Africa. Researchers collected data on 65 patients exhibiting various clinical features, including blood pressure, age, weight, history of hypertension and diabetes, and parity status. Several machine learning algorithms were applied, including logistic regression, support vector machine (SVM), naive Bayes, k-nearest neighbor, decision tree, and random forest. The evaluation results show that logistic regression has the best performance, with an accuracy and recall of 79.5% and 73.5%, respectively. In addition to evaluating prediction performance, this study emphasizes the importance of interpretability. The SHAP method was used to demonstrate the influence of each variable on the prediction [9].

In Padang City, the population totals for 2022 included 942,938 people, of whom 17,376 were pregnant women [10],[11]. In 2022, the maternal mortality rate due to pregnancy, childbirth, and the postpartum period was 17 cases per 100,000 live births, which was down from 30 cases in 2021. However, it rose again to 23 cases in 2023 [11]. Preeclampsia in pregnant women is one cause of maternal and infant mortality. Health workers strive to detect preeclampsia in pregnant women early on to ensure the safety and well-being of pregnant women, women in labor, and women in the postpartum period. According to the operational definition, around 20% of pregnant women are considered high risk, which includes those with preeclampsia.

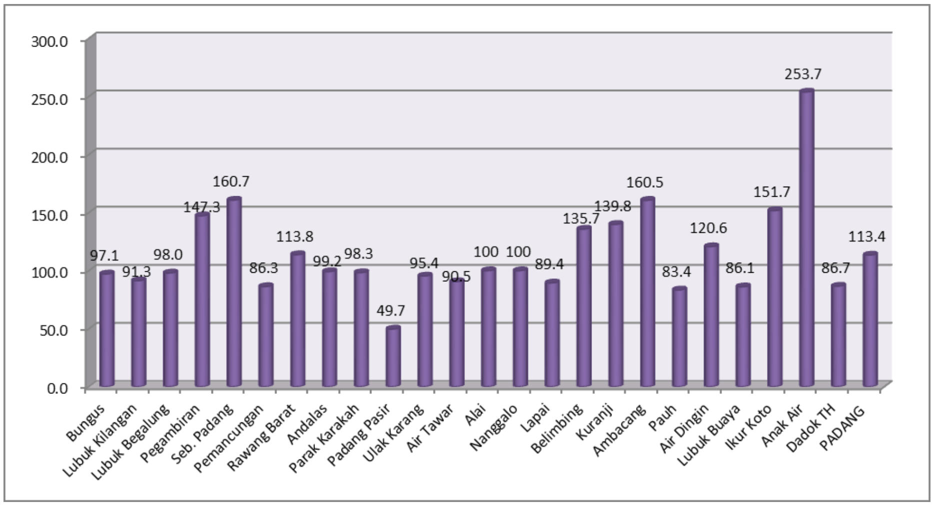

Figure1. Achievements in The Detection of High-Risk Pregnant Women by Health Workers in 2023

Source: [12]

Figure 1 shows that the detection rate of high-risk pregnant women in Padang City in 2023 is 113.4%. Community health center Anak Air in the Koto tangah district had the highest achievement at 253.7%, while Community health center Padang pasir had the lowest at 49.7%. The presentation of data on the detection of high-risk pregnant women shows that artificial intelligence technology has great potential to support decision-making, especially when it comes to predicting preeclampsia. One widely used method is machine learning that is a branch of artificial intelligence that allows computers to learn and make decisions or predictions without explicit programming [8], [9], [10].

Random Forest is one of the most popular machine learning algorithms [13], [14], A Random Forest is an ensemble algorithm that builds multiple decision trees in order to produce more accurate classifications and resist overfitting [15],[16],[17]. Random Forest is well-suited for handling large, complex datasets, making it ideal for medical data, which typically involves many variables [18],[[19],[20]. Random Forest is accurate and capable of handling complex data. However, it lacks transparency in interpretation [21],[22]. This is due to the model's structure, which consists of many decision trees. Each tree provides a prediction, which makes it difficult to explain the reasons behind a decision in detail[23].

The application of explainable artificial intelligence (XAI) has become very important [24],[25]. This study uses Random Forest to predict the risk of preeclampsia. The application of XAI can help to explain and understand the decision-making process of the model [26]. XAI is a subfield of AI that emphasizes creating models that clarify the logic behind predictions or decisions. XAI is important for improving transparency, trust, and accountability, particularly in high-impact applications like healthcare [25],[27],[28].

The goal of XAI is to bridge the gap between the predictive capabilities of models and the need for human-understandable interpretations[29]. This study employs SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) models. SHAP uses principles of game theory to measure how much each feature contributes to the predicted result[30], In the meantime, LIME is building simple local models to explain individual predictions [31]. Both approaches can help medical personnel clearly understand why the system generated the predictions it did.

The goal of this study is to design a preeclampsia prediction system that uses the Random Forest algorithm and is supported by the XAI method. The developed model can produce accurate predictions and provide understandable explanations of which features influence the results the most. This system can be a valuable tool for medical personnel at the Community health center Anak Air in Padang, providing them with clear interpretations to make quick clinical decisions and helping patients better understand their health conditions.

2. PRELIMINARIES

2.1 Machine Learning

Machine learning is an area of artificial intelligence which involves developing algorithms that can learn patterns from data and make predictions or decisions without being explicitly instructed to do so[32], [33], [34], [35]. This approach generally involves building mathematical models based on existing data and using them to process new data in order to make more objective decision [36], [37], [38], [39], [40]. Supervised learning is one important approach in machine learning [41], [42]. It is a training method that uses a labeled dataset. This dataset contains feature and target pairs as input and output, respectively, so the model can learn the relationship between them [43], [44]. The main objective is to find the most appropriate mapping function to minimize prediction errors. Classification tasks play an important role in the supervised learning framework because they are widely used to group data into specific categories [45], [46].

2.2 Random Forest

Random forest is an ensemble learning method that improves the accuracy and stability of predictions by combining multiple decision trees [47], [48]. Each tree is constructed using bootstrap sampling, also known as bagging, which involves taking random samples with replacement from the training dataset [49], [50]. Additionally, at each node of the tree, only a few features are randomly selected to determine the optimal separation. This strategy makes the model more resistant to overfitting and improves its ability to generalize [51], [52], [53].

2.3 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) is a branch of artificial intelligence that focuses on providing explanations for the decisions of complex machine learning models that are often considered black boxes, such as Random Forest, Gradient Boosting, and Deep Learning[54], [55]. The main purpose of XAI is to provide transparency and strengthen interpretability to build trust in the model. This ensures that the obtained prediction results are accurate and easily understood by researchers and end users [56], [57], [58], [59].

2.4 Shapley Additive Explanations (SHAP)

Shapley Additive Explanations (SHAP) is an Explainable Artificial Intelligence (XAI) approach that explains how much each feature contributes to a machine learning model's prediction [60], [61]. This method is rooted in Shapley value theory from cooperative game theory. In this theory, each feature is treated as a “player” that collectively produces the model output. The main principle of SHAP is to evaluate how prediction results change when a feature is added to or removed from a subset of other features [62]. In this way, SHAP offers a fair, consistent, and interpretable measure of each feature's role in the prediction process. Mathematically, the SHAP value for feature *i* is formulated as follows:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} \big(f(S \cup \{i\}) - f(S)\big) \qquad (1)$$

where ϕ_i is Shapley value, N is feature set, S is feature subset that does not include i, $|N|, |S|$ is number of elements in N and S, and $f(S \cup \{i\})$ is model prediction when *i* is added to S features.

2.5 Local Interpretable Model-agnostic Explanations (LIME)

Local Interpretable Model-agnostic Explanations (LIME) is an Explainable Artificial Intelligence (XAI) approach used to explain the results of complex, difficult-to-interpret machine learning models [63], [64]. The essence of LIME is building simple, easy-to-understand models, such as linear regressions or small decision trees, that mimic the behavior of the main model around specific data points [65], [66], [67]. LIME focuses solely on local explanations for a specific prediction. Thus, the interpretations provided are more relevant and appropriate to the conditions of the analyzed data. Mathematically, LIME formulates the problem as follows:

$$\xi(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) \quad + \Omega(g) \qquad (2)$$

where f is complex model (black box), g is interpretable model from a simple model set G, π_x is a local weight function that emphasizes samples around x point, $\mathcal{L}(f, g, \pi_x)$ is a loss function measures the suitability of g to f, and $\Omega(g)$ is regularization ensures that g remains simple.

2.6 Machine Learning Model Process

This study uses a machine learning model based on the Random Forest algorithm and an XAI approach to predict preeclampsia risk in pregnant women at the community health center Anak Air in Koto tangah district, Padang City. The modeling process is carried out in several systematic stages that is shown in Figure 2.

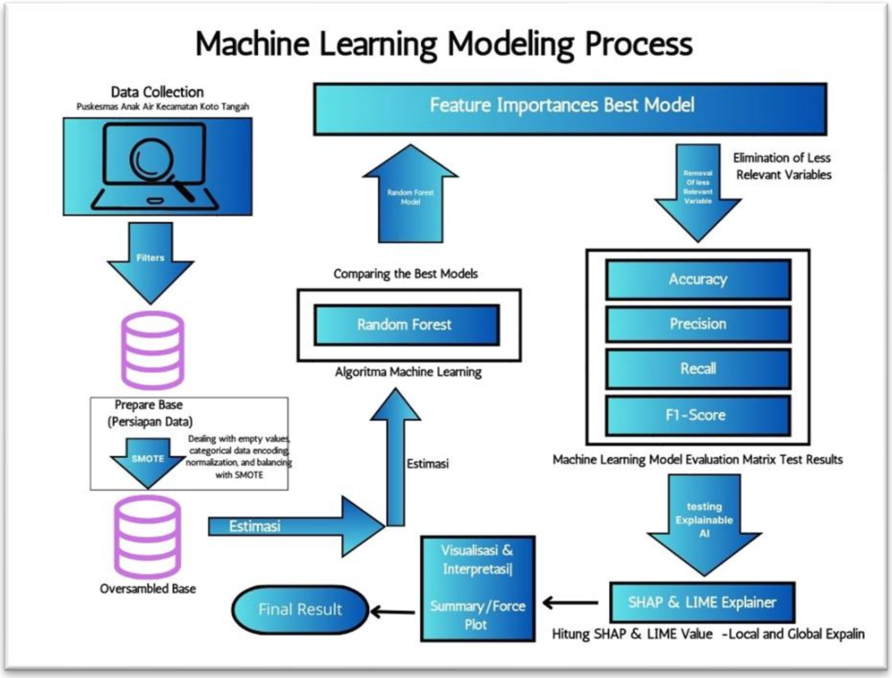

Figure 2. Machine Learning Model Process Flowchart for Predicting Preeclampsia Risk

1. Data Collection

This study used data from the community health centre Anak Air in the Koto tangah district. The data contains the medical information and clinical characteristics of pregnant women. The initial data will undergo a filtering stage to remove any incomplete, inconsistent, or irrelevant entries. The purpose of this stage is to ensure that the data is high-quality, accurate, and suitable for effective and valid further analysis in the machine learning model process.

2. Prepare Base Data

The data preprocessing stage includes several important steps: handling missing values; encoding categorical variables as numbers; normalizing to equalize the scale between features; and balancing class distribution using the SMOTE (Synthetic Minority Oversampling Technique) method. SMOTE increases the amount of data in minority classes by creating synthetic data [68]. The entire process is designed to create an oversampled base so that the machine learning model is not biased toward the majority class.

3. Model with Machine Learning Algorithms

The Random Forest model was chosen as the main algorithm for building the prediction system because it can overcome overfitting and handle high-dimensional data. A Random Forest model is formed by creating multiple decision trees using random subsets of the training data and features. The model then combines the prediction results from each tree to produce a final prediction based on majority voting for classification problems or averaging for regression problems.

4. Model Evaluation

We evaluate model performance using quantitative metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's ability to generate accurate predictions and maintain a balance between positive and negative case detection, particularly in unbalanced data sets. The model will be evaluated using the following metrics:

   a. Accuracy

   Accuracy is a measure of how often the model makes the correct prediction, compared to the total number of predictions it makes [69][70].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

   where TP = True Possitives, TN = True Negatives, FP = False Possitives, and FN = False Negatives.

b. Precision

Precision is a measure of how many of the model's positive predictions are correct, compared to the total number of positive predictions made by the model [72],[72].

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (4)$$

c. Recall

The recall rate (also known as the sensitivity rate or true positive rate) measures how many positive examples the model actually detects compared to the total number of examples in the dataset [73].

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (5)$$

d. F1-Score

The F1-score is a metric that balances precision and recall by combining them into a single value [74]. The F1-score is useful when there is class imbalance or when we want to consider both false positives (FP) and false negatives (FN) simultaneously.

$$\text{F1-Score}=\frac{2\text{TP}}{2\text{TP}+\text{FP}+\text{FN}} \qquad (6)$$

e. Feature Importance and Elimination

Feature importance and elimination analyze the level of importance of each feature in its contribution to the prediction. This process identifies the features with the greatest influence on the model output [47]. Features with low importance values are considered less relevant and eliminated from the model process. This elimination simplifies the model structure, reduces computational complexity, and improves interpretability without sacrificing prediction performance [75].

f. Explainable AI (XAI) Implementation

This study uses two methods, namely Shap and LIME, to improve the transparency and interpretability of the prediction model [77].

g. Visualization and Interpretation

The model interpretation process yields summary and force plots, which illustrate the contribution of features to the prediction results. The summary plot offers a broad view of how each feature influences the model's predictions, while the force plot provides specific explanations at the individual level.

h. Final Result

The final results of the estimation and interpretation process are compiled into comprehensive findings that support decision-making in medical contexts. This information is designed to help healthcare professionals detect the risk of preeclampsia earlier. This allows preventive measures and responses to be carried out more accurately and efficiently.

3. MAIN RESULTS

Data were collected using field research methods from pregnant women at the community health center Anak Air in Padang City. The data was then processed in Google Collaboratory with the Python programming language.

3.1 Dataset of Pregnant Women at the Community Health center Anak Air

This study used a total of 299 data sets from pregnant women in Anak Air, each of which had several predictor attributes: Age, systolic blood pressure (SBP), diastolic blood pressure (DBP), blood sugar, body temperature, heart rate, and protein in urine (mg/dL). Table 1 for an overview of the data used.

Table 1. Dataset of Pregnant Women at the Anak Air Community Health Center

	Age	Systolic BP	Systolic BP	Blood Sugar (BS)	Body Temp	Heart Rate	Protein Urine (mg/dl)	Risk Level
0	34	130	80	15.0	98	86	109.986450	High Risk
1	34	140	90	121.0	98	70	117.971904	High Risk
2	29	90	70	118.0	100	80	147.256969	High Risk
3	33	140	85	7.0	98	70	112.279872	High Risk
4	40	120	60	6.1	98	76	197.080530	Low risk

The target attribute or variable that is the goal of the classification is the Risk Level attribute, which indicates the risk level of preeclampsia. In the initial stage, the Risk Level value, which was originally categorical (low, mid, or high risk), was transformed into a numerical form using a label mapping process. Low risk was mapped to 0, medium risk to 1, and high risk to 2, which was intended to facilitate data processing by the system using classification algorithms.

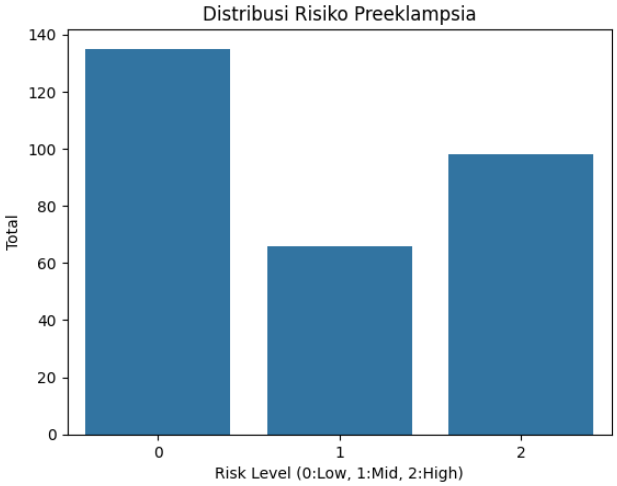

Figure 3. Distribution of Preeclampsia Risk Levels in the Initial Dataset

After the transformation, bar charts were used to visualize the class distribution and see how the data is distributed based on each risk level. As shown in Figure 3, the bar chart visualization results indicate that the amount of data with a low-risk label of 0 is the highest, followed by a high-risk label of 2, and finally a medium-risk label of 1. Figure 3 indicates that, although the data not perfectly balanced, it can still be used to train the classification model. Next, the model was trained and evaluated using the Random Forest Classifier algorithm to predict the risk level of preeclampsia based on available data. First, the model was trained using the training data, and then it was used to predict the data-test. The prediction results were then compared with the actual labels to measure the model's performance. Based on the displayed output, the model achieved an accuracy rate of 78%, meaning 78% of its predictions matched the actual data.

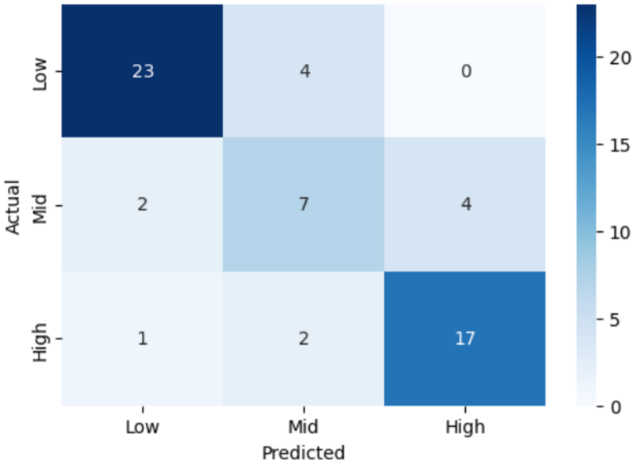

Figure 4. Confusion Matrix From Random Forest Model

The results of the confusion matrix and classification report from the Random Forest model show fairly good overall performance, with an accuracy rate of 78%, as illustrated in Figure 4. The model can classify most of the data correctly, especially the low and high classes, as shown in the confusion matrix. Of the 27 data points in the low class, 23 were classified correctly and four were incorrectly classified as mid. Of the 20 data points in the high class, 17 were classified correctly, two were classified as mid, and one was classified as low. However, the model performed less optimally for the mid class. Only seven out of thirteen data points were correctly classified; the remainder were incorrectly classified as low or high.

According to the classification report, the Low and High classes had the highest precision, recall, and F1-score values, with scores of 0.87 and 0.83, respectively. Meanwhile, the Mid class showed the lowest performance with precision, recall, and F1-score values of 0.54. The macro averages for precision, recall, and F1-score are 0.74, 0.75, and 0.75, respectively. These values reflect the model's overall performance without considering class distribution. The weighted average, which considers the amount of data in each class, shows values of 0.78 for precision, recall, and F1-score (Table 2).

Table 2. Classification Report for Preeclampsia Risk Prediction Model

	Precision	Recall	F1-Score	Support
0	0.88	0.85	0.87	27
1	0.54	0.54	0.54	13
2	0.81	0.85	0.83	20
Accuracy			0.78	60
Macro avg	0.74	0.75	0.75	60
Weighted avg	0.78	0.78	0.78	60

3.2 SHAP (Shapley Additive Explanations)

Once the model has been trained, the next step is to perform an interpretability analysis using the SHAP method to measure how each feature contributes to the model's prediction. The bar chart shows the absolute mean SHAP value of each feature, representing the magnitude of its influence on the classification result. The model predicts the risk level of preeclampsia in pregnant women, who are classified into three categories: low risk (class 0), moderate risk (class 1), and high risk (class 2).

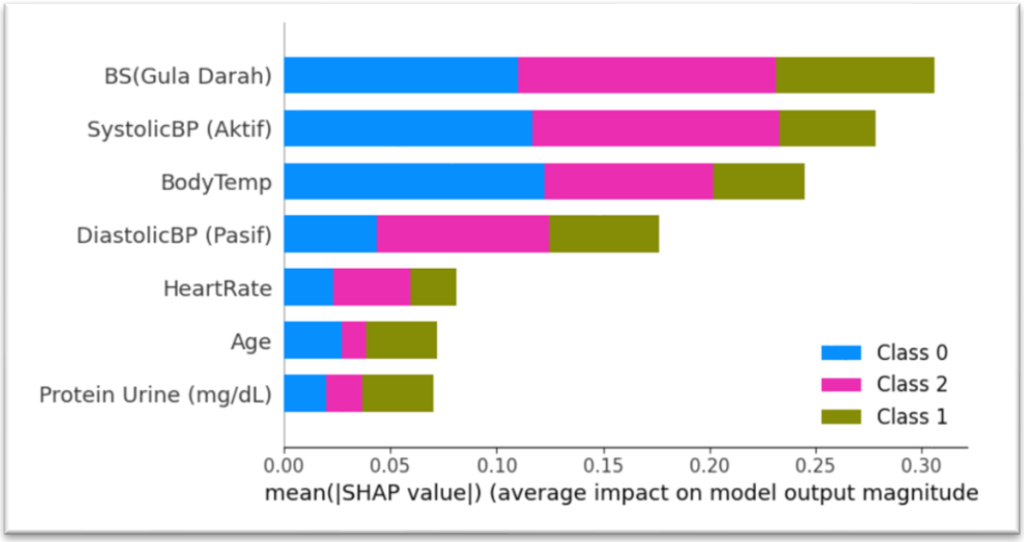

Figure 5. Visualization of SHAP Values for Interpreting the Preeclampsia Risk Prediction Model

Figure 5 illustrates the average absolute contribution of each feature to the Random Forest model's preeclampsia risk classification prediction. Blood sugar level has the greatest influence on the model and significantly impacts all three risk classes: low (Class 0), moderate (Class 1), and high (Class 2).

This shows that blood sugar is a very important indicator for determining preeclampsia risk levels. Systolic blood pressure (BP) and body temperature also contribute significantly, especially to the prediction of high-risk classes. Diastolic blood pressure contributes fairly evenly to the moderate and high risk classes, indicating that it is an important feature for distinguishing between the two.

Features such as Heart Rate have a greater influence on predictions for the moderate class, while Age and Urine Protein have less influence overall. However, urine protein significantly contributes to predicting the moderate class, so including it as an additional feature improves classification accuracy. Overall, the model considers various features in a balanced manner for each class, demonstrating good interpretability of the model in distinguishing pregnancy risk.

3.3 LIME (Local Interpretable Model-agnostic Explanations)

LIME is an explainable AI method that creates simple models to approximate the behavior of complex models around specific data, thereby explaining machine learning model predictions locally. Figure 6 shows the results of the interpretation of individual predictions using the LIME method for data point 0 in the test dataset.

Feature	Value
BodyTemp	101.00
DiastolicBP (Pasif)	60.00
BS(Gula Darah)	7.80
HeartRate	86.00
Protein Urine (mg/dL)	131.69

Figure 6. LIME Visualization for Interpretation of Individual Predictions of Preeclampsia Risk

The model predicts that this individual falls into the moderate risk category with a probability of 0.51. This is the highest probability compared to high risk (0.40) and low risk (0.09). Therefore, the model is most confident that the patient is in the moderate risk category. LIME identifies five features that contribute most to this prediction: body temperature (Body Temp), diastolic blood pressure (Diastolic BP), blood sugar level (BS), heart rate (Heart Rate), and protein level in urine (Protein Urine). The features that most strongly drive the prediction toward the moderate risk class are a high body temperature (101°F) and a low diastolic blood pressure (60 mmHg). Blood sugar levels of 7.80, a relatively high heart rate of 86 beats per minute (bpm), and high urine protein levels of 131.69 milligrams per deciliter (mg/dL) also contribute, though with smaller influences. This interpretation shows how the model uses specific medical values to make understandable, local predictions, which reinforces the added value of LIME in interpreting individual predictions.

4. CONCLUSION

This study shows that the Random Forest algorithm can provide fairly accurate predictions for classifying the risk level of preeclampsia in pregnant women, achieving an accuracy rate of 78%. The model performs well in distinguishing between low- and high-risk classes but less so for the moderate-risk class. This is largely due to the imbalance of the data used. Adding new features, such as urine protein levels, improves the model's interpretability, particularly in medium-risk classification. SHAP analysis reveals that blood sugar levels have the greatest influence on predictions, followed by systolic blood pressure and body temperature. Other features, such as heart rate, diastolic blood pressure, age, and urine protein, also contribute, albeit to a lesser extent. Meanwhile, the LIME method clearly shows why the model makes decisions in individual cases by displaying the specific combination of medical values that drive a particular classification. Overall, applying Explainable AI through SHAP and LIME provides a deep understanding of the model's prediction logic. This enables the results to serve as a basis for clinical decision-making in the early detection of preeclampsia in a transparent and trustworthy manner.

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CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest.

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