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Ensemble Techniques Based Risk Classification for Maternal Health During Pregnancy

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Abstract

This research focuses on the critical aspect of maternal health during pregnancy, emphasizing the need for early detection and intervention to address potential risks to both mothers and infants. Leveraging various classification methods, including Naïve Bayes, decision trees, and ensemble learning techniques, the study investigates the prediction of childbirth potential and pregnancy risks. The research begins with data collection, followed by preprocessing to clean and prepare the data, including handling missing values and normalization. Next, cross-validation is performed to ensure model robustness. Five ensemble techniques are used for risk classification: Ensemble Boosted Trees, which enhances the performance of decision trees; Ensemble Bagged Trees, which combines predictions from decision trees trained on different subsets of data; Ensemble Subspace Discriminant, which applies discriminant analysis on random subspaces; Ensemble Subspace KNN, which uses K-Nearest Neighbors (KNN) within random subspaces; and Ensemble RUS Boosted Trees. Key variables such as maternal age, height, Hb levels, blood pressure, and previous pregnancy history are considered in these analyses. Additionally, the study introduces Ensemble Learning based on Classification Trees, revealing significant improvements in accuracy compared to cost-sensitive learning approaches. The comparison of methods, including Naïve Bayes and K-Nearest Neighbor, provides insights into their respective performances, with ensemble techniques demonstrating their potential. The proposed ensemble learning techniques, namely Ensemble Boosted Trees, Ensemble Bagging Trees, Ensemble Subspace Discriminant, Ensemble Subspace KNN, and Ensemble RUS Boosted Trees, are systematically evaluated in classifying pregnancy risks based on a comprehensive dataset of 1014 records. The results showcase Ensemble Bagging Trees as a standout performer, with an accuracy of 85.6%, indicating robust generalization and effectiveness in clinical risk assessment compared to traditional methods such as Decision Tree (61.54% accuracy), K-Nearest Neighbor (74.48%), Ensemble Learning based on Cost-Sensitive Learning (73%), Ensemble Learning based on Classification Tree (76%), Gaussian Naïve Bayes (82.6%), Multinomial Naïve Bayes (84.8%), and Bernoulli Naïve Bayes (84.8%). Ensemble Bagging Trees achieved the highest accuracy proving to be more effective than the other methods. However, the study emphasizes the need for continuous refinement and adaptation of ensemble methods, considering both accuracy and interpretability, for successful deployment in healthcare decision-making. These findings contribute valuable insights into optimizing pregnancy risk classification models, paving the way for improved maternal and infant healthcare outcomes.

Keywords: Classification; Ensemble; Health Risk; Machine Learning; Maternal.

Introduction

Maternal health during pregnancy is a critical concern, with complications affecting millions of women worldwide [1]. According to the World Health Organization, approximately 830 women die from preventable causes related to pregnancy and childbirth every day, most of them in developing countries [2]. This highlights the urgent need for effective risk assessment methods to improve maternal and infant health outcomes [3]. Early detection of pregnancy risks is crucial for appropriate healthcare interventions, particularly in rural areas where lack of information leads to high incidences of complications [4]. Regular check-ups with midwives or doctors can help mitigate these risks, but more efficient predictive models are needed [5].

Research [6] proposes a classification method using Naïve Bayes to predict the potential childbirth of pregnant women, considering variables such as maternal age, height, Hb levels, blood pressure, previous pregnancy history, and underlying health conditions. The results show that the highest probability of childbirth is observed in region 1. Differences observed in the decision tree structure are primarily related to the initial nodes in each region, identified as the key factors influencing childbirth predictions. Divergence in program priorities in each region directly impacts the reduction of Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR), referring to variations in the initial

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nodes in each region. Research [7] applies the naïve bayes method for pregnancy risk classification, considering characteristics such as maternal age, number of children, height, pregnancy interval, previous miscarriages, vacuum extraction, cervical dilatation, infusion procedures, blood transfusion, cesarean section, blood deficiency, malaria, pulmonary tuberculosis, heart problems, diabetes, sexually transmitted diseases, facial swelling, twin pregnancies, twin types, miscarriages, overdue pregnancies, breech presentations, transverse presentations, bleeding, and seizures. The research findings indicate that the total probability calculation is performed by multiplying the probabilities of each class and attribute per class, then calculating the percentage of each class and comparing them; the class with the highest percentage becomes the pregnancy risk classification result. Research [8] proposes a Prediction Model for maternal health, considering variables such as age, blood pressure as SystolicBP, blood sugar as BS, diastolic blood pressure as DiastolicBP, heart rate, and body temperature. The research findings show that the best model performance is achieved using the decision tree algorithm with 15-fold cross-validation. Research [9] introduces a pregnancy risk classification approach using ensemble learning based on classification trees. The research findings show that implementing Poedji Rochyati's pregnancy risk classification using ensemble learning based on classification trees successfully improves the accuracy of the previous cost-sensitive learning approach. Specifically, for accuracy, ensemble learning achieves the highest value of 76%, while the cost-sensitive learning approach achieves the highest value of 73%. Meanwhile, for recall, ensemble learning achieves the highest value of 89.5%, compared to the cost-sensitive learning approach, which achieves the highest value of 77.9%. Research [10] considers the comparison of diabetes risk classification in pregnant women between Naïve Bayes and K-Nearest Neighbor (KNN) methods, taking into account variables such as Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, Diabetes Pedigree Function, Age, and Outcome. The research findings indicate that in data splitting using K-Fold Cross Validation with K=10, the Naïve Bayes algorithm yields a result of 75.78%, while using KNN with K=25 produces a result of 74.48%. From these results, it can be concluded that Naïve Bayes shows better performance compared to KNN. Research [11] proposes the classification of maternal health risks using machine learning methods. The results show that the accuracy of the algorithm models varies from 58.7% to 82.6%. Research [12] proposes a robust machine learning predictive model for maternal health risk. The proposed model has the potential for improved performance, with results showing that the Robust Model is the most efficient among traditional machine learning models with an accuracy of 70.21%.

Previous studies have proposed the use of data mining methods to classify birth risks [13], considering factors such as maternal age, height, Hb levels, blood pressure, previous pregnancy history, and underlying health conditions [14]. Other research has also applied data mining methods to classify pregnancy risks, considering various characteristics such as age, number of children, height, pregnancy interval, and other health conditions. However, research findings show variations in birth prediction outcomes and program priorities in different regions, especially ensemble learning, which relatively has lower accuracy results compared to other classification methods. Still, previous research has not tested ensemble techniques on ensemble model testing. Therefore, this research proposes the use of ensemble learning techniques [15], [16], including Ensemble Boosted Trees [17], [18], Ensemble Bagged Trees [19], [20], Ensemble Subspace Discriminant [21], Ensemble Subspace KNN [22], and Ensemble RUS Boosted Trees [23], to assess the accuracy of each ensemble technique in classifying pregnancy risks.

The data used in this research includes information on maternal health, categorized into three risk classes: low, moderate, and high [24]. Attributes considered involve maternal age, systolic and diastolic blood pressure, blood sugar levels, body temperature, and heart rate. This study aims to address a critical gap in existing research concerning pregnancy risk classification methodologies and the limitations inherent in current approaches. While prior studies have made strides in this field, they often overlook the potential of ensemble learning techniques, thereby failing to fully exploit the richness of predictive modeling. By delving into ensemble methods such as Ensemble Boosted Trees, Ensemble Bagged Trees, Ensemble Subspace Discriminant, Ensemble Subspace KNN, and Ensemble RUS Boosted Trees, this research endeavors to fill this void and pave the way for more robust and accurate pregnancy risk classification models.

The specific objectives of this research are twofold. Firstly, it seeks to rigorously evaluate the performance of ensemble learning techniques in the context of pregnancy risk classification. By conducting comprehensive experiments and analyses, the study aims to elucidate the strengths and weaknesses of these methods compared to traditional approaches. Secondly, it aims to undertake a systematic comparison between ensemble learning techniques and conventional methods commonly employed in pregnancy risk assessment. Through this comparative analysis, the research endeavors to highlight the potential benefits of adopting ensemble techniques in this domain.

The findings of this study hold significant promise for improving maternal and infant healthcare outcomes. By harnessing the power of ensemble learning, healthcare practitioners can potentially enhance the accuracy and reliability of pregnancy risk classification models. This, in turn, enables early identification of high-risk pregnancies, facilitating timely interventions and personalized care strategies. Moreover, by addressing the limitations of current methodologies, the research contributes to mitigating the challenges associated with pregnancy risk assessment, thereby fostering better healthcare delivery and ultimately improving maternal and infant health outcomes.

Method

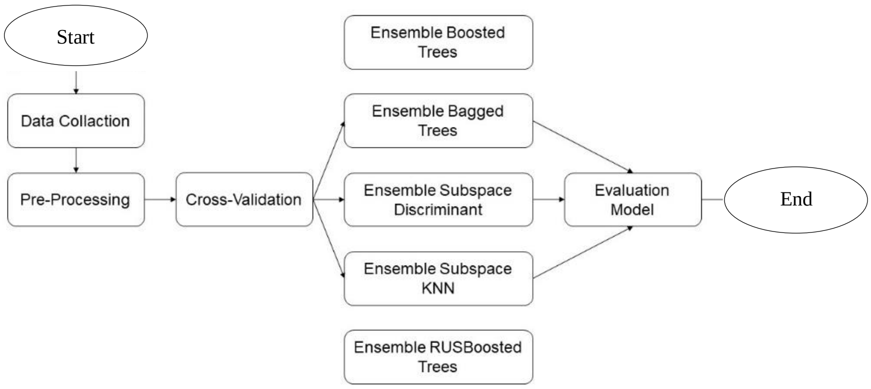

Figure 1. Research Stages

A. Data Collection

The process of Data Collection serves as a foundational and systematic activity crucial to the research endeavor, encompassing the deliberate gathering of information for subsequent analysis and interpretation [25]. In the context of this paper, the meticulous acquisition of data is orchestrated through the reputable UCI repository dataset site. Renowned for its credibility, this repository stands as a valuable resource housing a diverse array of datasets tailored to meet the specific requirements of various research pursuits.

The dataset selected for this study is carefully curated and specifically focuses on risk-related information pertinent to pregnant women. This deliberate choice aligns seamlessly with the research objectives, enabling a comprehensive exploration of the myriad factors that influence maternal health and associated risks. Leveraging the UCI repository enhances the robustness and validity of the research findings, given its reputation for hosting rigorously vetted datasets, ensuring the quality and reliability of the data integral to this study.

B. Preprocessing

Data Preprocessing is a crucial step in preparing data for classification algorithms [26], [27]. It involves stages like Data Cleaning to identify and rectify inconsistencies, errors, and outliers. The subsequent phase, Data Transformation, adapts the dataset for effective analysis by encoding categorical variables, creating new features, or normalizing skewed distributions. A key consideration is Data Normalization, ensuring values are standardized to a common scale, particularly important for features with varying magnitudes. In summary, Data Preprocessing streamlines the data for optimal use in classification algorithms.

C. K-Fold

K-Fold Cross-Validation is a widely used technique in machine learning and statistics for assessing the performance and generalizability of predictive models. In this method, the dataset is divided into k subsets, or folds, of approximately equal size. The typical choice for the value of k is 5 or 10, although other values can be used depending on the size and characteristics of the dataset. [28]. The process begins by partitioning the dataset into k equally sized folds. Then, for each iteration, one fold is set aside as the validation set, while the remaining k-1 folds are used as the training set. The model is trained on the training set and then evaluated on the validation set using a chosen performance metric, such as accuracy, precision, recall, or F1-score. This process is repeated k times, with each of the k folds used exactly once as the validation set. After all iterations are completed, the performance metrics obtained from each fold are averaged to obtain an overall estimate of the model's performance. This average performance metric serves as a more reliable indicator of the model's predictive capability compared to assessing it on a single validation set. Additionally, the standard deviation of the performance metrics across the folds can provide insights into the variability of the model's performance, further aiding in understanding its robustness. One of the key benefits of K-Fold Cross-Validation is that it provides a more accurate estimate of a model's performance by leveraging the entire dataset for both training and validation. This helps in reducing the variance in performance metrics that may occur due to random fluctuations in the data. Moreover, by systematically rotating through different subsets of the data, K-Fold Cross-Validation ensures that the model is evaluated on diverse samples, enhancing its ability to generalize well to unseen data. Furthermore, K-Fold Cross-Validation helps in mitigating the risk of overfitting by repeatedly training the model on different subsets of the data. This allows for a more comprehensive assessment of the model's ability to generalize to new, unseen data points. Overall, K-Fold Cross-Validation is a valuable technique for assessing the generalizability and robustness of predictive models, providing more reliable estimates of their performance and aiding in the selection of the best-performing model for deployment in real-world scenarios.

D. Ensemble Technique

1) Ensemble Boosted Trees

This technique involves the sequential construction of weak decision trees, usually stumps, where each subsequent tree focuses on rectifying the errors of its predecessors. By iteratively learning from the mistakes of previous models, Ensemble Boosted Trees enhances overall predictive performance. In the context of pregnancy risk classification, this method is particularly useful for capturing complex relationships between various risk factors and outcomes, thereby improving the accuracy of predictions [18].

2) Ensemble Bagged Trees

Ensemble Bagged Trees generate multiple decision trees through bootstrap sampling and aggregate their predictions through majority voting or averaging. This process helps in stabilizing the final prediction by reducing variance and overfitting. In pregnancy risk classification, Ensemble Bagged Trees can handle diverse data distributions and mitigate the impact of outliers, thus improving the robustness of the predictive model [20].

3) Ensemble Subspace Discriminant

This ensemble technique operates on variations of feature subsets or subspaces, where each model is constructed within a distinct subspace to accommodate diversity and address data complexity. Ensemble Subspace Discriminant is beneficial for capturing different aspects of the data and improving the model's generalization capability. In pregnancy risk classification, this method can effectively handle high-dimensional data and capture intricate patterns that may not be apparent in the full feature space [22].

4) Ensemble Subspace KNN

Ensemble Subspace KNN combines prediction outcomes from multiple KNN models constructed within different subspaces. By leveraging information from diverse perspectives, this approach aims to enhance KNN's performance in multidimensional data environments. In pregnancy risk classification, Ensemble Subspace KNN can improve the accuracy of predictions by considering various combinations of features and their respective neighborhoods [22].

5) Ensemble RUSBoosted Trees

This technique integrates principles from RUS Boost (Random Under-Sampling Boosting) and Boosted Trees, prioritizing the adaptive addressing of class imbalance during the learning process. Ensemble RUS Boosted Trees are particularly effective in scenarios where class distributions are skewed, such as in pregnancy risk classification where certain risk factors may be less prevalent. By dynamically adjusting the sampling strategy, this method can improve the model's ability to capture minority class instances and enhance overall predictive performance [29].

In the classification process, these ensemble techniques were integrated by combining the predictions of multiple models generated using each method. Ensemble-specific parameters such as the number of trees/stumps, subspace dimensions, and sampling strategies were carefully tuned to optimize performance. The rationale behind combining multiple ensemble methods lies in their complementary nature - each technique captures different aspects of the data and addresses specific challenges. By leveraging the strengths of each method, the overall accuracy and robustness of pregnancy risk classification can be significantly improved.

E. Performance Evaluation

To calculate the error value of the classification method, the confusion matrix is used so that the performance of the classification method can be evaluated as shown in **Table 1** [30].

Table 1. Confusion Matrix

Actual	**Prediction**		
	Low Risk	***Mid Risk***	***High Risk***
Low Risk	T_0	F_{01}	F_{02}
Mid Risk	F_{10}	T_1	F_{12}
High Risk	F_{20}	F_{21}	T_2

Description:

T_0 (True 0) : The actual value is zero, and the result of the prediction model is zero.

T_1 (True 1) : The actual value is one, and the result of the prediction model is one.

T_2 (True 2) : The actual value is two, and the result of the prediction model is two.

F_{01} (False 01) : The actual value is zero, and the result of the prediction model is one.

F_{02} (False 02) : The actual value is zero, and the result of the prediction model is two.

F_{10} (False 10) : The actual value is one, and the result of the prediction model is zero.

F_{12} (False 12) : The actual value is one, and the result of the prediction model is two.

F_{20} (False 20) : The actual value is two, and the prediction model result is zero.

F_{21} (False 21) : The actual value is two, and the result of the prediction model is one.

Accuracy indicates how close the measurement result is to the actual value. Calculating the accuracy using Equation 1.

$$accuracy = \frac{\sum_i T_i}{N} \quad (1)$$

Results and Discussion

The systematic classification of pregnant individuals into three discernible risk categories, specifically categorized as low-risk, mid-risk, and high-risk, constitutes the fundamental framework for the dataset under examination. This dataset is expansive, comprising a comprehensive total of 1014 individual records. Each record is intricately crafted to encapsulate a holistic set of attributes, reflecting a myriad of factors influencing maternal health. The intricate interplay of these attributes is visually represented in the illustrative **Figure 2** provided, which serves as a visual aid for understanding the multifaceted nature of the dataset.

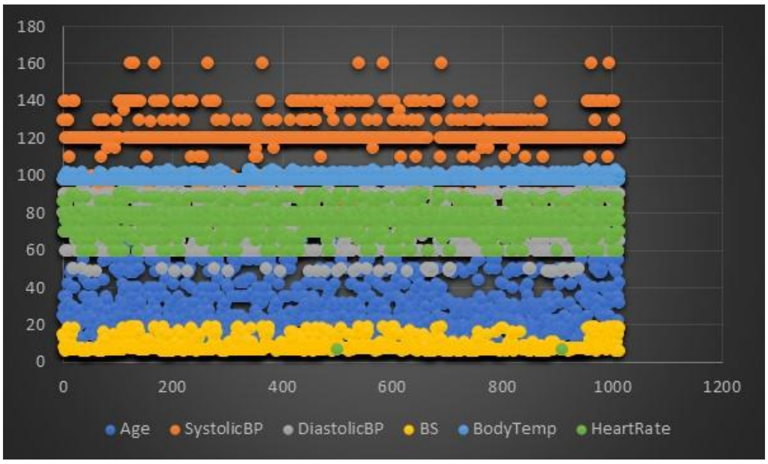

Figure 2. Comprehensive overview of maternal risk

Following this, the dataset containing risk-related information for pregnant women undergoes a meticulous processing phase, where cross-validation is systematically applied to partition the data into distinct sets for training and testing purposes. This meticulous approach is fundamental to ensuring the subsequent classification models' reliability and adaptability. The classification process encompasses the utilization of diverse ensemble techniques, specifically Ensemble Boosted Trees, Ensemble Bagged Trees, Ensemble Subspace Discriminant, Ensemble Subspace KNN, and Ensemble RUSBoosted Trees.

Ensemble Boosted Trees involves the sequential construction of multiple decision trees, each iteratively refining the predictive performance of its predecessor. In contrast, Ensemble Bagged Trees creates numerous decision trees through bootstrap sampling, amalgamating their predictions for heightened stability. Ensemble Subspace Discriminant operates within distinct feature subspaces, while Ensemble Subspace KNN combines predictions from multiple KNN models crafted within different subspaces to enhance performance in multidimensional data settings. Lastly, Ensemble RUSBoosted Trees integrates principles from RUSBoost and Boosted Trees, effectively addressing class imbalance during the learning process.

To unveil the outcomes of this classification endeavor, the study leverages the computational capabilities of Matlab, a renowned tool for data analysis and modeling. This comprehensive methodology aims to provide a nuanced understanding of the predictive capabilities of the ensemble techniques employed in the context of risk classification for pregnant women, ensuring a thorough and insightful analysis.

Table 2. Classification Results

Ensemble Method	Accuracy (%)
Ensemble Boosted Trees	72.6
Ensemble Bagging Trees	85.6
Ensemble Subspace Discriminant	63.6
Ensemble Subspace KNN	78
Ensemble RUSBoosted Trees	72.1

The comprehensive evaluation of ensemble methods for risk classification in pregnant women reveals diverse performance outcomes. Ensemble Boosted Trees displays a commendable accuracy of 72.6%, emphasizing its capacity to iteratively refine weak learners and enhance predictive power. However, further scrutiny is needed to address potential misclassifications and optimize parameters for improved performance. Ensemble Bagging Trees stands out with an impressive accuracy of 85.6%, showcasing robust generalization and effective mitigation of overfitting. Its efficacy in handling diverse datasets positions it as a promising candidate for practical applications in clinical risk assessment for pregnant women, though considerations regarding model interpretability and computational efficiency should be taken into account.

Conversely, Ensemble Subspace Discriminant exhibits a slightly lower accuracy of 63.6%, indicating potential challenges in capturing the multifaceted nature of risk factors within chosen feature subspaces. A comprehensive exploration of feature selection methods and subspace configurations is essential for optimizing accuracy. Ensemble Subspace KNN performs commendably with an accuracy of 78%, demonstrating proficiency in handling multidimensional data. Hyperparameter fine-tuning and additional feature engineering techniques could further enhance its accuracy. Ensemble RUS Boosted Trees achieves a competitive accuracy of 72.1%, highlighting its effectiveness in addressing class imbalance, yet a more granular examination is necessary for optimizing boosting parameters and exploring ensemble size variations.

Overall, Ensemble Bagging Trees emerges as a frontrunner, indicating its potential for immediate practical deployment in risk assessment for pregnant women. However, continuous refinement and adaptation of ensemble methods, considering both accuracy and interpretability, are essential for their successful deployment in healthcare decision-making. These findings provide a foundational understanding for ongoing optimization efforts and underscore the need for a nuanced and iterative approach to model development in the context of risk classification for pregnant women.

Table 3 Comparison of Maternal Health Classification Outcomes

Author	Classification	Accuracy (%)
H. Amalia	Decision Tree	61.54
B. Delvika, et.al	K-Nearest Neighbor	74.48
Poedji Rochyati	Ensemble Learning based on cost sensitive learning	73
M.A. Hidayat	Ensemble Learning based on Classification Tree	76
NF. Mustamin	Gaussian Naïve Bayes	82.6
	Multinomial Naïve Bayes	84.8
	Bournolli Naïve Bayes	84.8
Proposed	Ensemble Boosted Trees	72.6
	Ensemble Bagging Trees	85.6
	Ensemble Subspace Discriminant	63.6
	Ensemble Subspace KNN	78
	Ensemble RUSBoosted Trees	72.1

The analysis of various classification models for predicting pregnancy-related risks provides valuable insights into the diverse methodologies employed. H. Amalia's Decision Tree model yielded an accuracy of 61.54%, indicating potential limitations in capturing the complexity of pregnancy risk factors. B. Delvika, et.al's K-Nearest Neighbor demonstrated a moderate accuracy of 74.48%, suggesting reasonable performance in predicting risks based on neighboring data points. Poedji Rochyati's Ensemble Learning model, based on cost-sensitive learning, achieved a competitive accuracy of 73%, showcasing the effectiveness of combining multiple models. M.A. Hidayat's Ensemble Learning model, specifically based on Classification Trees, outperformed counterparts with an accuracy of 76%, highlighting the strength of ensemble techniques. NF. Mustamin's Naïve Bayes models (Gaussian, Multinomial, and

Bournolli) consistently demonstrated high accuracies, ranging from 82.6% to 84.8%. Among the proposed ensemble models, Ensemble Bagging Trees stood out with an impressive accuracy of 85.6%, emphasizing robust generalization capabilities. However, Ensemble Subspace Discriminant exhibited a lower accuracy of 63.6%, indicating potential challenges in capturing multifaceted risk factors. In conclusion, the analysis underscores the effectiveness of ensemble techniques, particularly Ensemble Bagging Trees, in predicting pregnancy risks, with continuous refinement essential for successful deployment in healthcare decision-making.

Conclusion

In conclusion, the study extensively evaluated ensemble learning techniques for classifying pregnancy risks, highlighting Ensemble Bagging Trees as the most effective method with an impressive accuracy of 85.6%. This emphasizes the superiority of ensemble methods over traditional classifiers and underscores their potential in enhancing pregnancy risk assessment. The findings hold significant implications for improving maternal and infant healthcare outcomes by enabling early detection and intervention for high-risk pregnancies. Ensemble learning techniques offer a robust framework for accurately identifying pregnancy risks, thereby facilitating personalized care strategies and ultimately improving healthcare delivery for pregnant women and infants. However, the study's limitations, including potential biases in the dataset and challenges in model interpretability, may impact their direct application in clinical practice. Future research should focus on addressing these limitations by exploring additional ensemble learning techniques, expanding datasets to include more diverse populations, and investigating the impact of socioeconomic factors on pregnancy risk classification. Continuous refinement and adaptation of ensemble methods are crucial for their successful integration into clinical practice and healthcare decision-making processes.

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