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Ensemble-Based Model for Predicting Maternal Health Risk in Southwest Nigeria

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Abstract

Maternal mortality remains a critical public health concern, particularly in Nigeria, which continues to report one of the highest maternal death rates globally. This study proposes an innovative approach for predicting maternal health risks by integrating primary clinical data with a rule-based classification system and ensemble machine learning techniques. A dataset of 148 records was obtained from Ondo State University Teaching Hospital, encompassing key maternal health indicators. Given the lack of predefined class labels, a rule-based labeling framework adapted from a publicly available Kaggle dataset was applied. The data underwent preprocessing, including imputation for missing values and balancing using the Synthetic Minority Over-sampling Technique (SMOTE). Three ensemble machine learning models Voting, Stacking, and Bagging were developed and evaluated based on accuracy, precision, recall, and F1-score. Results showed that SMOTE markedly enhanced classification performance, with the Stacking ensemble achieving the highest accuracy (94.6%) and precision (97.1%). These outcomes highlight the potential of machine learning to enable early detection of maternal health risks and support improved decision-making in clinical settings.

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Keywords: Maternal Mortality; Rule-Based Classification; Machine Learning Techniques; SMOTE; Ensemble Models

INTRODUCTION

Maternal health encompasses the physical, mental, and emotional well-being of a woman throughout pregnancy, childbirth, and the postpartum period. Maternal morbidity and mortality rates associated with pregnancy are critical public health indicators, reflecting the accessibility and quality of maternal and general healthcare services. Several risk factors must be continuously monitored during pregnancy, including maternal age, systolic and diastolic blood pressure, body temperature, heart rate (pulse), blood oxygen level, and respiratory rate. The integration of machine learning algorithms to analyze these parameters enables early detection of potential complications, thereby reducing maternal and neonatal mortality rates and enhancing maternal health outcomes [1], [2]

As of 2020, Nigeria recorded a maternal mortality rate of 1,047 deaths per 100,000 live births, ranking among the highest in Africa [3]. Primary complications contributing to maternal mortality and morbidity during pregnancy and childbirth include severe hemorrhage, infections, hypertensive disorders, delivery-related complications, and unsafe abortion. Additional contributing factors encompass cardiovascular conditions, diabetes, anemia, and mental health disorders such as depression and anxiety [4]. Therefore, Early identification of pregnancy-related complications through regular, high-quality medical examinations—particularly for high-risk pregnancies—before, during, and after childbirth is essential for reducing maternal morbidity and mortality.

This research makes the following key contributions:

1. Primary Data Collection: Gathers original data on maternal health from a university teaching hospital to support evidence-based analysis.
2. Rule Generation Using a Rule-Based Approach: Applies a rule-based method to extract meaningful patterns from an existing maternal health dataset sourced from Kaggle, aiding in the determination of risk levels within the collected data.
3. Classification with Ensemble-Based Models: Implements ensemble learning techniques to classify the maternal health dataset, enhancing predictive accuracy and robustness.

4. Performance Evaluation: Conducts a comprehensive performance assessment of the classification results to validate the effectiveness of the proposed approach.

Related Works

Ayesha & Sultana (2023) developed classification model on Maternal Health Risk Analysis. The objectives of this research is to analyze the risk to a mother's health using exploratory data analysis and machine learning algorithms and compare the analysis result with some existing results to get better prediction. The researcher collected records which include independent variables (age, systolic BP, diastolic BP BS, body temp, heart rate), and Risk Level characteristic as the independent variable. Five supervised learning techniques (Gaussian Naive Bayes, Support Vector Machine (SVM), Xgboost, Random Forest, and Decision Tree), was employed to build a predictive model to determine the maternal health risk level classes (high or low). The result shows that Xgboost, Decision Tree and Random Forest have 94% accuracy, Support Vector Machine algorithm has 72% accuracy and Naıve Bayes has 64% accuracy respectively. The limitation is that more algorithms and more dataset can be used to build more accurate model [5].

Taofeeq *et al.* (2023) worked on deep hybrid model for maternal health risk classification in pregnancy using ANN and Random Forest. Artificial neural networks (ANN) and random forest (RF) algorithms were adopted to build model to improve the accuracy and efficiency of risk classification in pregnant women. The dataset used in this study consists of variables like; age, systolic and diastolic blood pressure, blood sugar, body temperature, and heart rate. The dataset is divided into training and testing sets, with 75% of the data used for training and 25% used for testing. The output of the ANN and RF classifier is considered, and a maximum probability voting system selects the output with the highest probability as the most correct. Performance is evaluated using various metrics, such as accuracy, precision, recall, and F1 score and the results showed that the developed model achieves 95% accuracy, 97% precision, 97% recall, and an F1 score of 0.97 on the testing dataset [6].

Sulaiman *et al.* (2024) worked on Predicting maternal risk level using machine learning models. The researchers explored the potential of machine learning (ML) algorithms in maternal risk level prediction using a nationwide maternal mortality dataset from Oman. The researchers used a total of 402 maternal deaths from 1991 to 2023 in Oman, used principal component analysis (PCA) in the machine learning (ML) algorithms and compared them to the results of model performance without PCA. Ten ML algorithms, including decision tree (DT), random forest (RF), K—Nearest Neighbors (KNN), Naïve Bayes (NB), Extreme Gradient Boosting (xgboost), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Logistic Regression (LR), Support Vector Machine (SVM) and Artificial Neural Network (ANN) were adopted and compared. The Different metrics, including, accuracy, sensitivity, precision, and the F1- score, were utilised to assess model performance and the results shows that the Random Forest model outpaced the other methods in predicting the risk level (low or high) with an accuracy of 75.2%, precision of 85.7% and F1- score of 73% after PCA was applied. The limitation of this research is that the researchers used secondary data and no clinical features were included for predicting maternal mortality risk levels. In conclusion, a reliable estimate of maternal risk level would facilitate intervention plans for medical practitioners to reduce maternal death [7].

Alaa, *et al.* (2024) designed an ensemble machine learning framework for predicting maternal health risk during pregnancy. The researcher employed four ensemble ML techniques to develop predictive model using a real-world datasets. The dataset collected from various maternity hospitals and clinics were subjected to nineteen training and testing tests using exploratory data analysis and it was discovered that the most significant risk factors for pregnant women are high blood pressure, low blood pressure, and high blood sugar levels and all variables in the dataset were strongly correlated and have been shown to help in predicting maternal health risks. The result shows that gradient boosted trees (GBT) with the ensemble stacking approach outperformed and demonstrated outstanding performance for all evaluation measures (0.86) for all classes available in the dataset. The limitation of this work is that the dataset has a limited number of features and that the dataset needs modification which could help to improve the performance of the suggested system [8].

Aman *et al.* (2024) worked on Predicting Maternal Health Risk using Machine Learning Models and Comparing the Performance of Percentage Split and K-Fold Cross Validation. The aim of this study is to develop a predictive model to sight the effectiveness of different model architectures and evaluate their performance using percentage split and K-Fold cross validation. In this research, five different algorithms of machine learning techniques (Support Vector Machine (SVM), Logistic Regression, Decision Trees Classifier k-Nearest Neighbors (KNN) and XGBoost) were explored and evaluated. Two types of models were developed for each algorithm: one employing a traditional approach, and another incorporating k-fold cross-validation. The performance of these algorithms under varying conditions was obtained and the findings from these evaluations provide valuable insights into the effectiveness of these models by shedding light on their respective strengths and weaknesses [9].

Similarly, Hursit, *et al.* (2023) investigated the Prediction of Maternal Health Risk with Traditional Machine Learning Methods. In this study, six different machine learning techniques were adopted to determine maternal health risk of gravid women. The researchers collected data from different places using IoT-based risk monitoring systems. The dependent variables in this dataset include age, systolic BP, diastolic BP, blood sugar, and heart rate characteristics, while the independent variable is the level of risk which is classified into three categories (high risk, middle risk, and low risk). The results obtained from the developed models were compared with each other and it was observed that the most successful method in estimating maternal risk health was Decision Tree. The accuracy value obtained in the Decision Tree method was 89.16% and the lowest accuracy rate among the methods used in the paper was obtained in the k-nearest neighbors (KNN) method with 68.47% [10] .

Sulis, *et al* (2020) investigated maternal complications and risk factors for mortality. The aim of this study was to analyse maternal complications and the possible high-risk factors connected to maternal mortality. The researchers conducted a case-control study to investigate the causes of maternal mortalities amongst pregnant, delivering, and postpartum mothers between 2017 and 2018. A total sample size of 48 samples was selected through simple random sampling. The result of logistic regression analysis showed nutritional status, prominence of anemia, history of illness, age, antenatal care ANC examination, method of delivery, late referral, occupational status, as well as postpartum complications, as the most influencing risk factors. This very high significance for maternal mortality was based on the chi-square value of 109.431 (p equal to 0.000), and R square (0.897). Finally, the potential risk factors of maternal mortality were identified and these include nutritional status, state of anemia, history of illness, age, ANC examination, delivery method, late referral, occupational status, and pregnancy complications, which is specifically the most dominant factor [11] .

Ajayi *et al.* (2025) worked on Predicting Maternal Health Risks Using Machine Learning: A Comparative Study of Classification Algorithms. The aim of this study is to explore the potential of machine learning techniques in predicting maternal health risks. The dataset used in this study is from Kaggle.com and contains 1,014 instances with seven attributes: age, systolic blood pressure, diastolic blood pressure, blood sugar level, body temperature, heart rate, and risk level. Three machine learning techniques (Random Forest, Support Vector Machines, and K-Nearest Neighbors) were trained and evaluated. The Random Forest classifier emerged as the best-performing model, achieving an accuracy of 80.79%, along with superior precision, recall, and F1-score. Performance evaluation using confusion matrices confirmed its effectiveness in distinguishing maternal risk levels. These findings highlight the potential of machine learning for early risk assessment [12].

The research identifies a significant gap in the application of machine learning to maternal health prediction, particularly the lack of studies using primary data collected from hospital settings. Most existing works rely heavily on secondary datasets with predefined labels, limiting their practical applicability. Furthermore, previous studies often overlook the issue of class imbalance, which can affect model accuracy, especially in detecting high-risk cases. This study addresses these gaps by implementing a rule-based labeling approach to classify unlabeled primary data and employing ensemble learning techniques with SMOTE-based class balancing, offering a more robust and clinically relevant solution for maternal health risk prediction.

METHODOLOGY

The methodological steps employed in this study are depicted in the framework below. It outlines the key processes undertaken to achieve the study's results. These include data acquisition, preprocessing, class balancing, dataset partitioning, ensemble based classificati on, and model evaluation.

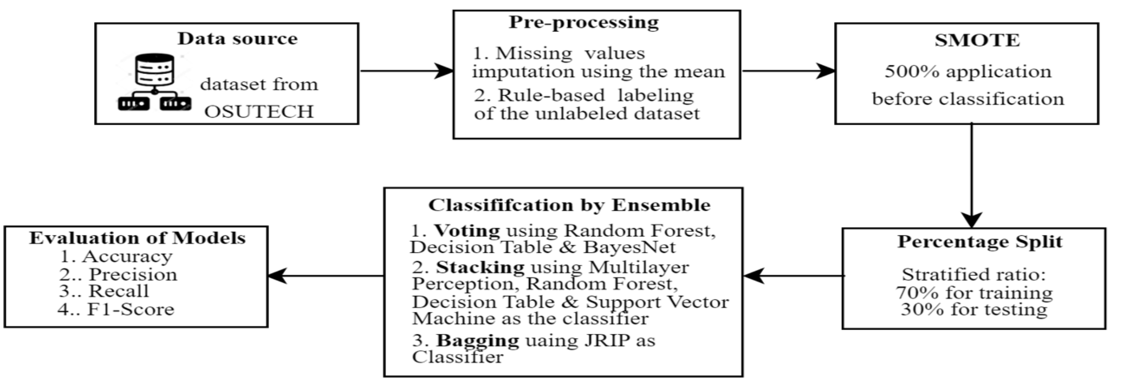


Figure 1: Maternal Health Prediction Framework

Data Source

This study utilized primary data obtained from Ondo State University Teaching Hospital (OSUTECH). A total of 148 records were collected, each comprising seven features: Age, Systolic Blood Pressure, Diastolic Blood Pressure, Body Temperature, Heart Rate, Weight, and Height. Notably, the dataset did not include any predefined class labels.

To facilitate labeling, a set of classification rules, as illustrated in Figure 2, was developed through the analysis of a publicly available maternal health dataset from Kaggle. These rules were derived by identifying patterns and relationships within the labeled Kaggle dataset, which served as a reference framework for the labeling process. A summary of the dataset features is provided in Table 1. The generated rules are as follows:

- SystolicBP ≥ 129.5
- DiastolicBP ≥ 92.5 AND HeartRate ≥ 66.5
- BodyTemp ≥ 100 AND Age ≥ 22 AND DiastolicBP ≤ 75
- Age ≤ 50 AND DiastolicBP = 80
- SystolicBP =120 AND (DiastolicBP = 75 OR DiastolicBP = 85 OR DiastolicBP = 90) AND BodyTemp = 98
- BodyTemp ≥ 100 AND DiastolicBP ≥ 65
- BodyTemp ≥ 100 AND HeartRate ≤ 66.7
- HeartRate ≥ 79 AND Age ≥ 22.5

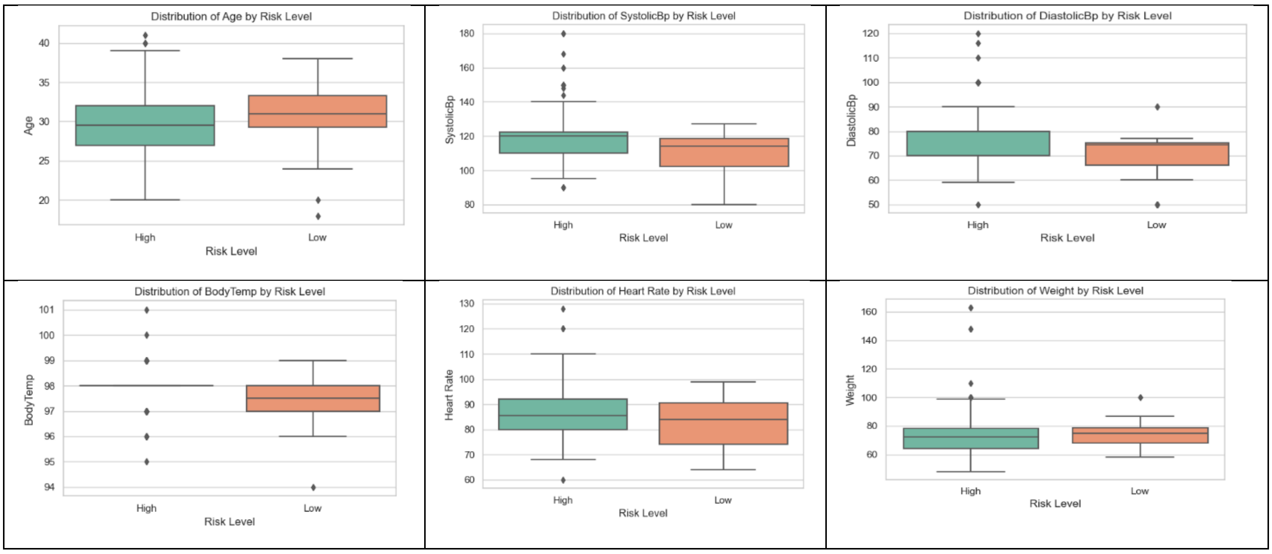
Figure 2: Rules generated from the Kaggle maternal health dataset.

Table 1: Dataset Description

Feature	Description
Age	The number of years a woman has lived, recorded during pregnancy.
Stytolic	The upper measurement of blood pressure in millimeters of mercury (mmHg)
Diastolic	The lower measurement of blood pressure in millimeters of mercury (mmHg),
Temperature	The body internal heat balance
Heart Rate	The typical resting heart rate, counted in beats per minute.
Weight	The measure of human body mass
Height	The vertical measurement of the body
Risk level	The anticipated intensity of risk during pregnancy, based on the above attributes

Statistical Analysis of features

Statistical analysis tools are useful for uncovering key information that guides the choice of suitable preprocessing techniques before building a model. Table 2 shows the statistical summary of the dataset's numerical features, including the mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, maximum, and the count of missing values for each attribute. In addition to this, the distribution plots is also presented in Figure 3



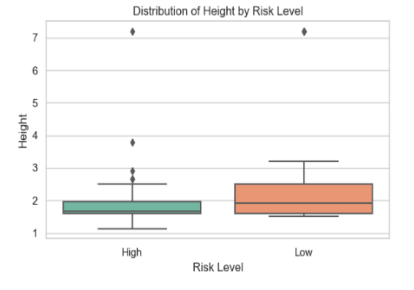


Figure 3: Distribution Plots of the features

Table 2: Statistical Analysis of features.

	Mean	Standard	Minimum	25%	50%	75%	Maximum	Missing
Age	29.77027	16.999054	18	27	30	32.25	41	1
Stytolic	118.1081	16.999054	80	110	120	120	180	1
Diastolic	74.35811	11.712549	50	70	70	80	120	3
Temperature	36.58	0.4560702	34.5	36.375	36.6	36.8	38.6	13
Heart Rate	86.55405	10.334069	60	80	84.5	92	128	3
Weight	75.11486	17.749015	48	64.75	74	78.25	163	21
Height	1.961689	0.9441365	1.13	1.59	1.67	1.96	7.2	21

Preprocessing

Preparing data for analysis requires transforming unprocessed data into a clean, structured format suitable for modeling. In this study, the dataset collected from OSUTECH lacked predefined class labels. To address this, a rule-based strategy was employed to assign class labels, categorizing records into High and Low risk groups. The classification rules were formulated by referencing a labeled maternal health dataset sourced from Kaggle. These rules were developed based on identifiable trends and correlations observed in the Kaggle dataset concerning maternal health risks. The derived rules were then systematically applied to the unlabeled hospital dataset. Each entry was assessed using the established conditions, and a label—either HIGH or LOW—was assigned accordingly. This process enabled the conversion of the unlabelled data into a format suitable for further analysis and predictive modeling. As a result, out of 148 total records, 128 were classified as HIGH risk and 20 as LOW risk.

Moreover, the existence of missing values in a dataset can significantly affect analysis outcomes. They may reduce the reliability of statistical inferences, introduce estimation bias, and complicate the analytical process. To address this issue in the current study, missing values in numerical attributes were treated using mean imputation. This approach is illustrated in Equation (1):

$$\bar{X} = \frac{\sum X}{n} \qquad (1)$$

Where $\bar{X}$ represents the mean, X denotes an individual data point and n is the total number of observations:

Class balancing and percentage split

To handle missing data within the dataset, mean imputation was employed to replace absent numerical values with the corresponding feature averages. To address class imbalance, the Synthetic Minority Over-Sampling Technique (SMOTE) was applied at a 500% oversampling rate, effectively increasing the number of Low risk instances and producing a more balanced distribution—comprising 128 High risk and 120 Low risk records. Subsequently, the refined dataset was partitioned into training and testing subsets using a stratified 70:30 split to preserve class proportions during model evaluation.

Description of proposed techniques:

This section describes the ensemble techniques used for the classification:

Voting Ensemble: The Voting Ensemble combined predictions from Random Forest, Decision Trees, and BayesNet classifiers.

Performance Metric

This study employed several standard evaluation metrics to assess the performance of the trained models. These metrics were selected based on the attributes incorporated in the proposed model and include the Confusion Matrix—a two-dimensional table that illustrates the relationship between actual and predicted classes—as well as Accuracy, Precision, Recall, and F1-Score. The formulas for these metrics are presented in Equations (i) to (iv) below.

$$\text{accuracy} = \frac{instances\ correctly\ classified\ as\ HR + instances\ correctly\ classified\ as\ LR}{Total\ number\ od\ instances} \qquad (i)$$

$$\text{precision} = \frac{instances\ correctly\ classified\ as\ HR}{instances\ correctly\ classified\ as\ HR + instan} \qquad (ii)$$

$$\text{recall} = \frac{instances\ correctly\ classified\ as\ HR}{instances\ correctly\ classified\ as\ HR + instances\ of\ HR\ incorrectly\ classified\ as\ LR} \qquad (iii)$$

$$\text{F1-score} = 2 * \left(\frac{precision*recall}{precision+recall}\right) \quad \text{(iv)}$$

where HR implies instance with high risk level while LR implies instance with low risk level

RESULTS AND DISCUSSION

Table 3 below presents the performance evaluation of three ensemble models (Voting, Stacking, and Bagging) applied to maternal health prediction tasks, both with and without the use of Synthetic Minority Over-sampling Technique (SMOTE). Without the application of SMOTE, the Voting and Bagging ensemble models demonstrate comparable performance, each achieving a Precision of 79.1%, Recall of 97.1%, and an F1-Score of 87.2%, outperforming the Stacking ensemble in these metrics. These results suggest that both models are highly effective at identifying true positive cases—specifically, high-risk maternal health conditions. However, the relatively lower precision indicates a higher occurrence of false positives, where non-risk cases are incorrectly classified as high risk. The accuracy scores of the models: 77.3% for Voting and Bagging, and 72.7% for Stacking are modest, likely reflecting the impact of class imbalance in the dataset. This imbalance can skew the model's learning process, making it more difficult to correctly classify less frequent but critical cases.

Table 3: Performance Evaluation Results

Models	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
WITHOUT SMOTE				
Voting Ensemble	79.10	97.10	87.20	77.30
Stacking Ensemble	78.0	91.4	84.10	72.70
Bagging Ensemble	79.10	97.1	87.20	77.30
WITH SMOTE				
Voting Ensemble	89.50	94.40	91.90	91.90
Stacking Ensemble	97.10	91.70	94.30	94.60
Bagging Ensemble	91.9	94.4	93.1	93.2

With the application of SMOTE, the performance of all ensemble models improves significantly. The Voting ensemble achieves a precision of 89.5%, a recall of 94.4%, and an F1-score of 91.9%, with its accuracy rising to 91.9%. These results indicate a well-balanced model with fewer false positives and enhanced generalization capabilities. The Stacking ensemble records the highest precision at 97.1%, an F1-score of 94.3%, and an accuracy of 94.6%, demonstrating its strong ability to distinguish between different maternal health risk levels in a balanced dataset. Similarly, the Bagging ensemble performs robustly, with a precision of 91.9%, recall of 94.4%, and an F1-score of 93.1%. This indicates a reliable and balanced model suitable for real-world maternal health risk prediction.

In maternal healthcare, the timely and accurate identification of high-risk cases is crucial for reducing maternal and neonatal mortality and enhancing overall health outcomes. Models with high recall are particularly important, as they minimize the likelihood of missing true high-risk cases—an outcome that could have severe consequences. At the same time, achieving high precision is equally critical to prevent unnecessary strain on healthcare resources caused by false positive alerts.

The integration of SMOTE (Synthetic Minority Over-sampling Technique) significantly enhances model performance by addressing class imbalances commonly found in maternal health datasets. By generating synthetic examples of underrepresented cases, SMOTE enables models to better learn the patterns associated with rare but high-risk conditions. Consequently, ensemble models augmented with SMOTE, particularly Stacking and Bagging, demonstrate greater predictive accuracy and reliability. These characteristics make them highly suitable for practical deployment in maternal healthcare settings, where the stakes of misclassification are exceptionally high.

CONCLUSION

This study introduces a robust framework for predicting maternal health risks by integrating primary clinical data with a rule-based classification approach and ensemble machine learning techniques. Leveraging classification rules extracted from a publicly available Kaggle dataset, the researchers successfully labeled previously unclassified real-world data from a Nigerian teaching hospital—enhancing both the practical relevance and analytical depth of the study. The deployment of ensemble models (Voting, Bagging, and

Stacking) yielded notable improvements in predictive performance, particularly when data imbalance was mitigated using the Synthetic Minority Over-sampling Technique (SMOTE). Among these, the Stacking model emerged as the most effective, achieving a precision of 97.1% and an accuracy of 94.6%, thereby highlighting the critical role of data preprocessing in healthcare analytics.

By addressing limitations in prior research—such as the reliance on secondary data and the neglect of class imbalance—this work bridges the gap between theoretical machine learning models and their application in real-world clinical settings. The findings affirm the value of ensemble learning, especially on balanced datasets, in supporting timely and accurate maternal health risk assessments. Such predictive capabilities are vital in healthcare environments, where early identification of high-risk conditions can significantly improve maternal outcomes. Future research will extend the classification to multiple risk levels (LOW MEDIUM, and HIGH) using deep learning techniques to enhance the model's precision and decision-making capabilities.

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