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A Comparative Analysis of Supervised Learning Methods in Maternal Health Risk Detection

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ABSTRACT: Maternal health risk refers to conditions that endanger a pregnant woman's well-being and require timely assessment to prevent complications. Early identification of such risks is crucial for effective intervention. In this study, we applied and compared three machine learning algorithms Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) to predict maternal health risk levels during pregnancy. The dataset, collected through an IoT-based monitoring system from rural hospitals and maternal healthcare centres in Bangladesh, included six input features: age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and heart rate. The target variable, risk level, was categorized into three classes: low, mild, and high. Results show that RC achieved the highest accuracy (85.21%), with balanced sensitivity and specificity, making it the most effective model for early detection. RFC also performed competitively and can serve as a reliable alternative. By contrast, NNge, although effective in identifying low-risk cases, showed lower overall accuracy and higher misclassification, limiting its suitability for critical maternal health decisions. These findings highlight RC as the most promising approach for supporting healthcare providers in timely maternal risk management.

Keywords: Maternal health risk, Randomizable Filtered Classifier, Random Committee

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تحليل مقارن لأساليب التعلم المُشرف في الكشف عن مخاطر صحة الأم

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المستخلص:
يشير خطر صحة الأم إلى الحالات التي تهدد رفاهية المرأة الحامل وتتطلب تقييماً مبكراً لتجنب المضاعفات وضمان التدخل الفعّال. يُعَدّ الكشف المبكر عن هذه المخاطر أمراً أساسياً لتعزيز فرص التدخل الناجح. في هذه الدراسة، تم تطبيق ومقارنة ثلاثة خوارزميات من تقنيات التعلّم الآلي وهي: لجنة عشوائية(Random Committee - RC) ، المصنف العشوائي المصفى (Randomizable Filtered Classifier - RFC)، وأقرب جار مع التعميم (Nearest Neighbor with Generalization - NNge) للتنبؤ بمستويات مخاطر صحة الأم أثناء فترة الحمل. جُمعت البيانات من خلال نظام مراقبة قائم على إنترنت الأشياء (IoT) في مستشفيات ريفية ومراكز رعاية الأمومة في بنغلاديش، وقد تضمنت ستة متغيرات إدخالية هي: العمر، ضغط الدم الانقباضي، ضغط الدم الانبساطي، مستوى السكر في الدم، درجة حرارة الجسم، ومعدل ضربات القلب. أما المتغير المستهدف (مستوى الخطر) فقُسِّم إلى ثلاث فئات: منخفض، معتدل، وعالٍ. أظهرت النتائج أن خوارزمية اللجنة العشوائية (RC) حققت أعلى دقة (85.21%) مع توازن جيد بين الحساسية والنوعية، مما يجعلها النموذج الأكثر فعالية للكشف المبكر. كما أظهر المصنف العشوائي المصفى (RFC) أداءً

تنافسياً ويمكن اعتباره بديلاً موثوقاً. في المقابل، وعلى الرغم من أن خوارزمية أقرب جار مع التعميم (NNge) كانت فعّالة في تحديد الفئة منخفضة الخطورة، إلا أنها سجلت دقة أقل ومعدلات خطأ أعلى، مما يقلل من ملاءمتها لاتخاذ القرارات الطبية الحساسة التي تتطلب تحديداً دقيقاً للحالات عالية الخطورة. تؤكد هذه النتائج أن خوارزمية اللجنة العشوائية (RC) تُعدّ النهج الأكثر وعداً لدعم مقدمي الرعاية الصحية في الإدارة المبكرة لمخاطر صحة الأم.

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Introduction

Maternal health risk remains a significant public health concern globally, particularly in low-resource regions where access to quality prenatal care is limited. The World Health Organization (2022) reports that approximately 295,000 women die annually from pregnancy-related complications, with most cases being preventable through timely diagnosis and intervention. Early detection of maternal health risks such as gestational hypertension, diabetes, and abnormal heart rates can significantly improve outcomes for both the mother and fetus. Key physiological indicators such as age, blood pressure, blood sugar, body temperature, and heart rate are vital in assessing maternal risk levels during pregnancy. Traditional assessment methods often depend on manual clinical evaluations, which can be slow and prone to human error. With advancements in healthcare technology, innovative solutions—such as real-time data collection through wearable sensors and automated data analysis using machine learning—enable continuous and more accurate monitoring of maternal health indicators, improving the prediction and management of pregnancy-related risks. In particular, applying machine learning (ML) techniques to clinical data has emerged as a reliable and scalable method for identifying at-risk pregnancies, even in remote or underserved areas (Khatun et al., 2021). ML can analyze vast datasets, discover complex patterns, and provide early warnings to healthcare providers, enhancing clinical decision-making. Therefore, integrating ML algorithms into maternal health risk assessment not only supports early detection but also enables resource optimization in overburdened healthcare systems. This study aims to explore the application of selected machine learning algorithms for predicting maternal risk levels and identifying the most effective model for use in real-world maternal healthcare contexts. Machine learning (ML) is a subset of artificial intelligence that enables systems to learn from data patterns and improve predictive performance without being explicitly programmed. It plays a crucial role in healthcare, especially in diagnostics and risk prediction, by automating decision-making processes based on historical clinical data (Obermeyer & Emanuel, 2016). ML models are typically trained on labeled datasets and validated using techniques such as cross-validation to ensure generalizability. Classification algorithms in ML are particularly useful for categorizing patients into health risk levels based on physiological variables. Popular algorithms include decision trees, ensemble methods, and instance-based learning techniques. This study applies three distinct ML classifiers Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) to a maternal health dataset collected from rural healthcare facilities. These algorithms are evaluated in terms of accuracy, precision, recall, and F1-score to identify the most effective approach for classifying maternal health risks.

A demonstration of the working machine is shown in Figure 1. Once the suitable classification algorithm become used to in finding the appropriate one for predicting Maternal Health Risk.

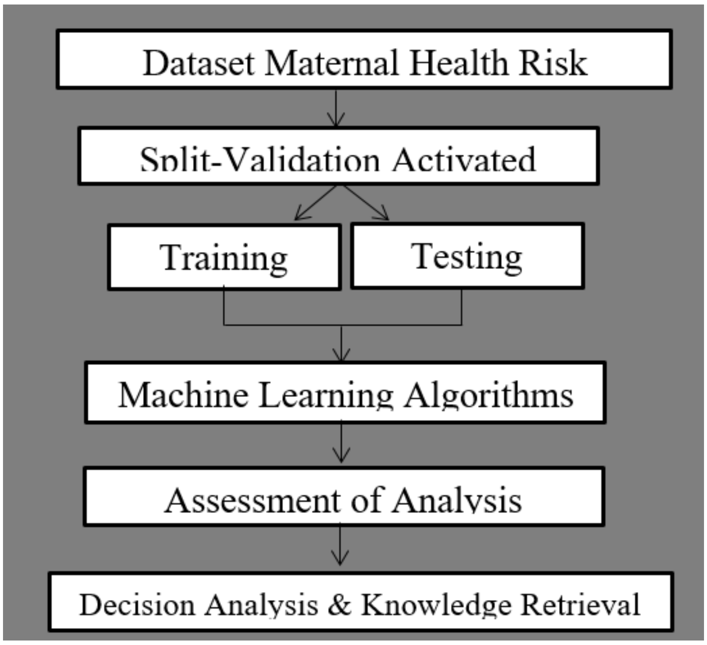

Figure (1): working process

The Random Committee (RC) algorithm is an ensemble-based machine learning technique that combines multiple base classifiers to improve prediction accuracy and model stability. It operates by generating several instances of a base classifier, each trained with different random seeds, and then averages their outputs to make final predictions (Witten et al., 2016). This approach helps reduce variance and mitigates the risk of overfitting, making RC particularly suitable for complex classification tasks in medical data. In the context of maternal health, RC can effectively analyze multiple physiological indicators simultaneously and produce robust risk level predictions. By leveraging the strength of multiple models, RC offers more reliable performance than a single classifier. Its ease of implementation within platforms like Weka also makes it an accessible tool for healthcare researchers seeking to explore ensemble learning techniques in clinical applications (Hall et al., 2009). RC averages the outputs of M classifiers trained with different random seeds:

$$f_{RC}(x) = \frac{1}{M}\sum_{i=1}^{M} f_i(x) \qquad (1)$$

Where:

M : number of base classifiers and $f_i(x)$: prediction of the i^{th}classifier

The Randomizable Filtered Classifier (RFC) is a meta-classifier in Weka that applies preprocessing filters to datasets before passing them to a base classifier. This flexible design allows for noise reduction, attribute selection, or data normalization before training, enhancing model performance in diverse datasets (Witten et al., 2016). RFC is especially useful when dealing with clinical data, where preprocessing steps can significantly impact classification accuracy. On the other hand, Nearest Neighbor with Generalization (NNge) is a hybrid rule-based and instance-based algorithm. It constructs generalized exemplars from training instances, which reduces storage requirements while maintaining high accuracy. Unlike standard k-nearest neighbor methods, NNge focuses on interpretability and rule extraction, making it well-suited for medical applications where model transparency is critical (Clark & Niblett, 1989). Both classifiers offer unique strengths for healthcare diagnostics and are tested in this study for maternal health risk classification. RFC applies a preprocessing filter $T(.)$ on the input data before passing it to a base classifier C

$$f_{RFC}(x) = C(T(x)) \qquad (2)$$

Where:

$T(x)$: transformation of input (filtering, normalization, feature selection, etc.)
C: base classifier function

Nearest Neighbor with Generalization (NNge) is a machine learning algorithm that merges aspects of lazy learning and rule-based classification. Developed by Clark and Niblett (1989), NNge differs from traditional k-nearest neighbor (KNN) algorithms by generating generalized prototypes referred to as exemplars rather than storing all training data. This not only reduces memory usage but also enhances model interpretability through the creation of rule-like structures. NNge is particularly beneficial in medical domains where explainability and transparency are essential for trust and adoption. In maternal health prediction, NNge can identify complex relationships between physiological features and risk levels while allowing healthcare professionals to understand the underlying rules driving predictions. Its generalization ability makes it resilient to noise, improving its robustness in real-world health datasets. NNge generalizes instances into exemplars (rule-based regions). Classification is based on the nearest exemplar E_j

$$f_{NNge}(x) = \arg min_{E_j \in E}\, d(x, E_j) \qquad (3)$$

Where:
E : set of generalized exemplars and $d\left(x, E_j\right)$: distance between instance x and exemplar E_j

In this study, the selection of Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) was based on their complementary strengths in handling healthcare data. RC was chosen because ensemble methods are particularly effective for complex medical datasets, reducing overfitting and improving prediction stability. RFC was included due to its ability to incorporate preprocessing filters such as noise reduction and normalization, which are crucial when dealing with heterogeneous clinical data collected from multiple healthcare facilities. Finally, NNge was selected because of its rule-based generalization approach, which not only reduces storage and computational requirements but also enhances interpretability—an important factor in medical decision-making where healthcare providers need to understand the reasoning behind predictions. Together, these three classifiers represent diverse methodological approaches (ensemble, meta-classifier with preprocessing, and rule-based generalization), allowing for a robust comparative analysis of maternal health risk prediction.

2.Purposes of the Research.

The main objective of this study is to assess and compare the performance of three machine learning algorithms Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) in predicting maternal health risk levels based on six key physiological parameters. This evaluation aims to determine the most accurate and reliable model for supporting early diagnosis and decision-making in maternal healthcare systems.

3.Materials and Methods

The dataset used in this study was collected from various hospitals, community clinics, and maternal healthcare centres located in rural regions of Bangladesh, utilizing a technology-supported monitoring system designed to track maternal health risks. The study used clinical information from 1014 patients. This system enabled real-time acquisition of patient data, ensuring accurate and timely information collection. The dataset includes six explanatory (independent) variables: X1 (Age), X2 (Systolic Blood Pressure), X3 (Diastolic Blood Pressure), X4 (Blood Sugar), X5 (Body Temperature), and X6 (Heart Rate). The response variable (Y: Risk Level) categorizes the maternal health status into three levels: low, mild, and high risk. To analyze and predict these risk levels, three machine learning algorithms Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) were applied. These algorithms were executed and tested using the Weka machine learning platform. Model performance was assessed through cross-validation, employing metrics such as accuracy, precision, recall, and F1-score. The results provide a comparative evaluation of each algorithm's effectiveness in accurately classifying maternal health risk levels

4. Performance Evaluation

In multi-class classification, such as predicting maternal health risk levels categorized as Low, Mild, and High, the confusion matrix expands to a 3×3 table. It compares actual versus predicted risk classes and helps evaluate how well the classifier distinguishes between the different levels of risk. Each cell indicates the number of instances where a class was predicted for another, allowing performance assessment across all categories. Table 1 shows the structure of the confusion matrix, while Table 2 presents the key performance metrics such as Accuracy, Precision, Recall, F-Measure, and Matthews Correlation Coefficient (MCC) computed per class. These metrics provide a comprehensive understanding of the classifier's strengths and weaknesses in detecting each risk level.

Table (1) Confusion Matrix

Actual / Predicted	Low	Mild	High
Low	TP (Low)	FN(Low→Mild)	FN (Low→High)
Mild	FN (Mild→Low)	TP (Mild)	FN(Mild→High)
High	FN (High→Low)	FN(High→Mild)	TP (High)

Table (2) Detailed Accuracy by Classes

Metric	Explanation (per class)
Accuracy	(TP (Low) + TP (Mild) + TP (High)) / Total number of instances × 100
Precision (Low)	TP (Low) / (TP (Low) + FN (Mild→Low) + FN (High→Low)) × 100
Precision (Mild)	TP (Mild) / (TP (Mild) + FN (Low→Mild) + FN (High→Mild)) × 100
Precision (High)	TP (High) / (TP (High) + FN (Low→High) + FN (Mild→High)) × 100
Recall / Sensitivity (Low)	TP (Low) / (TP (Low) + FN (Low→Mild) + FN (Low→High)) × 100
Recall / Sensitivity (Mild)	TP (Mild) / (TP (Mild) + FN (Mild→Low) + FN (Mild→High)) × 100
Recall / Sensitivity (High)	TP (High) / (TP (High) + FN (High→Low) + FN (High→Mild)) × 100
F1 Score (per class)	2 × (Precision × Recall) / (Precision + Recall) × 100 (calculated separately for Low, Mild, and High classes)
Macro Average F1 Score	Average of F1 Scores for all three classes (Low, Mild, High)
Micro Average Accuracy	Same as overall Accuracy; based on total correct predictions across all classes
MCC (per class)	Uses TP, FP, TN, FN for each class vs. all others; computed per class with binary formulation
ROC Area (per class)	Area under ROC curve for each class (TPR vs. FPR); based on predicted probabilities

5. Analysis and Discussion

This study uses a dataset from 1014 patients in rural Bangladesh to track maternal health risks. The dataset includes six independent variables and categorizes maternal health status into low, mild, and high risk levels. Machine learning algorithms Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) were applied to analyse and predict these risk levels. The results provide a comparative evaluation of each algorithm's effectiveness. Machine learning algorithms were used in Weka

5.1 Confusion Matrix for Machine learning algorithms

Table (3): Classification Results of Machine Learning Algorithms Based on Confusion Matrix

Algorithms	Actual Class of Maternal Health Risk	Predicted Class of Maternal Health Risk			
		Low	Mild	High	Total
RC	Low	249	10	13	272
	Mild	11	334	61	406
	High	21	34	281	336
	Total	281	378	355	1014
RFC	Low	245	12	15	272
	Mild	16	329	61	406
	High	19	36	281	336
	Total	280	377	357	1014
NNge	Low	238	10	24	272
	Mild	11	336	59	406
	High	17	50	269	336
	Total	266	396	352	1014

Table (3) presents the performance of three machine learning algorithms—Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge)—in classifying maternal health risk levels into three categories: Low, Mild, and High, based on data from 1014 patients. The Random Committee algorithm correctly classified 249 out of 281 Low-risk cases, demonstrating strong performance with minimal misclassification (10 Mild, 13 High). For Mild risk, RC correctly predicted 334 out of 406 cases but misclassified 61 as High, indicating some challenge in distinguishing between Mild and High risk levels. In the High-risk group, RC identified 281 out of 336 cases correctly, with 34 misclassified as Mild and 21 as Low. Overall, RC showed good accuracy with balanced classification across all classes. The Randomizable Filtered Classifier performed comparably, correctly classifying 245 Low-risk, 329 Mild-risk, and 281 High-risk cases, with similar misclassification patterns to RC. Nearest Neighbor with Generalization had lower accuracy, correctly classifying 238 Low-risk and 269 High-risk cases but showed slightly better results for Mild risk with 336 correct predictions. It exhibited the highest misclassification rates, particularly in distinguishing High-risk cases. Overall accuracy was highest for RC at approximately 85.21%, followed by RFC at 84.30%, and NNge at 83.17%. These results suggest that ensemble-based classifiers like RC and RFC provide better accuracy and reliability for maternal health risk prediction compared to NNge in this dataset.

5.2 Classification Accuracy, Sensitivity and Specificity of Proposed

Table (4): Performance Metrics of Classifiers

Metric	RC	RFC	NNge
Accuracy	85.21%	84.32%	83.14%
Correctly Classified	864 out of 1014	855 out of 1014	843 out of 1014
Sensitivity (Low)	91.50%	90.10%	87.50%
Sensitivity (Mild)	82.30%	81.00%	82.80%
Sensitivity (High)	83.60%	83.60%	80.10%
Specificity (Low)	95.70%	95.35%	96.23%
Specificity (Mild)	92.80%	92.11%	90.13%
Specificity (High)	89.10%	88.79%	87.75%

Table (4) presents a detailed comparison of the classification performance of three machine learning algorithms RC, RFC, and NNge in predicting maternal health risk levels (Low, Mild, and High). The comparison includes essential performance metrics such as accuracy, correctly classified instances, sensitivity, and specificity for each risk category. Accuracy serves as a primary performance indicator, reflecting the overall correctness of the model across all classes. The Random Committee (RC) algorithm achieved the highest accuracy at 85.21%, correctly classifying 864 out of 1014 instances. This result highlights RC's strong predictive ability across the dataset. Randomizable Filtered Classifier (RFC) follows closely with an accuracy of 84.32%, classifying 855 cases correctly, which indicates a comparable performance to RC with only a marginal drop. Nearest Neighbor with Generalization (NNge) achieved the lowest accuracy of 83.14%, correctly classifying 843 instances, suggesting slightly weaker overall prediction capability relative to the ensemble-based classifiers (RC and RFC). In terms of class-wise sensitivity, which measures the model's ability to correctly identify positive cases within each risk category, RC and RFC show consistent performance, particularly for the High-risk group, both achieving 83.60% sensitivity. RC also excels in the Low-risk category with 91.50%, indicating strong detection of patients at minimal risk. NNge, while competitive in the Mild-risk category (82.80%), showed reduced performance in identifying High-risk cases (80.10%), a critical shortfall in clinical applications where misclassifying high-risk pregnancies can have serious consequences. Regarding specificity, which reflects the model's ability to correctly identify negative cases (non-risk cases), NNge slightly outperforms both RC and RFC in the Low-risk category (96.23%), suggesting that it is highly effective in identifying true negatives for this group. However, its overall lower sensitivity and accuracy diminish the advantage. RC maintains better balance between sensitivity and specificity, indicating a more reliable and consistent performance across risk levels.

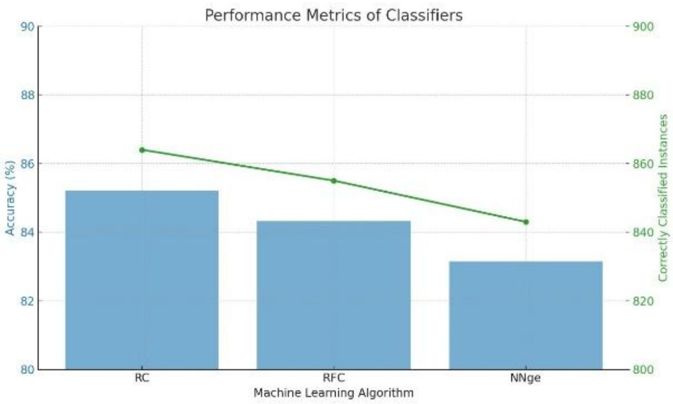

Figure (2) Shows the Classification Accuracy between Algorithm

5.3 Calculation Detailed Performance Metrics

Table (5) Comprehensive Performance Metrics by Class for Classifiers

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
RC	Low	0.823	0.072	0.884	0.823	0.852	0.76	0.947	0.913
	Mild	0.836	0.109	0.792	0.836	0.813	0.718	0.944	0.887
	High	0.915	0.043	0.886	0.915	0.901	0.863	0.973	0.946
	Weighted Avg.	0.852	0.077	0.854	0.852	0.852	0.774	0.953	0.913
RFC	Low	0.81	0.079	0.873	0.81	0.84	0.742	0.919	0.893
	Mild	0.836	0.112	0.787	0.836	0.811	0.714	0.932	0.815
	High	0.901	0.047	0.875	0.901	0.888	0.846	0.956	0.929
	Weighted Avg.	0.843	0.081	0.845	0.843	0.843	0.76	0.933	0.877
NNge	Low	0.828	0.099	0.848	0.828	0.838	0.732	0.864	0.771
	Mild	0.801	0.122	0.764	0.801	0.782	0.671	0.839	0.678

	High	**0.875**	**0.038**	**0.895**	**0.875**	**0.885**	**0.843**	**0.919**	**0.816**
	Weighted Avg.	**0.831**	**0.09**	**0.833**	**0.831**	**0.832**	**0.741**	**0.871**	**0.752**

The table presents a detailed performance comparison of three classifiers—RC, RFC, and NNge—across three classes: Low, Mild, and High. The true positive (TP) rates for all classifiers are generally high, indicating good sensitivity, with the High class consistently achieving the highest TP rates (RC: 0.915, RFC: 0.901, NNge: 0.875). False positive (FP) rates are relatively low across classes, particularly for the High class, reflecting strong specificity. Precision values demonstrate that RC slightly outperforms the other classifiers, especially in the Low and High classes (0.884 and 0.886 respectively), suggesting it is better at minimizing false positives. The F-measure, which balances precision and recall, also favors RC with a weighted average of 0.852 compared to RFC's 0.843 and NNge's 0.832, indicating a better overall balance of classification performance. The Matthews Correlation Coefficient (MCC), which considers true and false positives and negatives, further supports RC's superior predictive power with a weighted average of 0.774. Additionally, RC achieves the highest ROC Area (0.953) and PRC Area (0.913), metrics reflecting overall discrimination capability and precision-recall trade-off. In summary, while all classifiers show competitive performance, the RC classifier demonstrates marginally better accuracy, reliability, and discrimination across classes in this dataset.

6 Discussion

This study evaluated the performance of three machine learning algorithms—Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge)—in predicting maternal health risk levels in a dataset of 1014 patients from rural Bangladesh. The RC algorithm demonstrated the highest overall accuracy (85.21%) and correctly classified the greatest number of cases (864), outperforming RFC (84.32%) and NNge (83.14%). This indicates that ensemble-based methods such as RC and RFC offer superior predictive power compared to instance-based methods like NNge in this clinical context. The RC also showed better sensitivity across all risk categories, particularly excelling in identifying Low-risk cases (91.5%) and High-risk cases (83.6%), which is crucial for timely intervention in maternal healthcare. Although NNge exhibited higher specificity in the Low-risk category, its lower sensitivity and accuracy make it less suitable for identifying high-risk pregnancies where false negatives could have serious health implications. Performance metrics including precision, F-measure, and Matthews Correlation Coefficient further favored RC, demonstrating its robustness and balanced classification ability. Moreover, RC achieved higher ROC and PRC areas, reflecting superior discrimination capability and reliability. Overall, the results highlight the effectiveness of ensemble classifiers like RC for maternal health risk prediction, supporting their application in clinical decision support systems.

7 Conclusions and recommendations

7.1 Conclusion

This research confirms that machine learning algorithms can effectively classify maternal health risk levels using clinical data. Among the three algorithms tested Random Committee (RC), Randomizable Filtered Classifier (RFC), and Nearest Neighbor with Generalization (NNge) RC emerged as the most reliable and accurate model. The Random Committee algorithm achieved the highest accuracy at 85.21%, correctly classifying 864 out of 1014 instances, demonstrating its strong predictive ability across the dataset. RFC followed closely with an accuracy of 84.32%, correctly classifying 855 cases, indicating comparable performance with only a slight decrease. NNge showed the lowest accuracy at 83.14%, correctly classifying 843 cases, reflecting relatively weaker prediction capability compared to the ensemble-based classifiers RC and RFC.

Beyond accuracy, RC outperformed the other algorithms in sensitivity and specificity across all risk categories Low, Mild, and High offering superior balance between precision and recall. This balanced performance is especially important in the identification of High-risk pregnancies, where correct classification is critical for timely clinical intervention. While RFC also showed robust performance, NNge's comparatively lower sensitivity and overall accuracy highlight limitations in its use for critical maternal health risk prediction.

These findings underscore the effectiveness of ensemble methods like RC in maternal health risk assessment, emphasizing the importance of selecting robust algorithms tailored to healthcare applications. Future research should explore integrating additional clinical variables and larger datasets to enhance predictive accuracy and support improved maternal health outcomes.

7.2 Recommendations

Based on the study's findings, it is recommended that healthcare providers and policymakers prioritize the adoption of ensemble machine learning models like Random Committee to support maternal health risk assessment. Implementing these models in clinical decision support tools can improve early identification of at-risk pregnancies, enabling timely interventions and resource allocation. Additionally, further research should explore the inclusion of more comprehensive clinical and demographic variables to enhance predictive accuracy. Training healthcare staff on the interpretation and integration of such AI-driven tools is also essential to maximize their benefit in real-world maternal health settings.

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