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Prediction of Maternal Health Risk Using Clinical and Physiological Indicators in Rural Bangladesh: A Machine Learning Study

Dr. Lalit Kumar Singh[1],Dr. Kiran Srivastava[2]

[1]Lalit Kumar Singh, Associate Professor, Department of Psychiatry, PGIMER -Chandigarh, Email: Llt_kumar@yahoo.com, Orcid ID: https://orcid.org/0000-0002-7145-5155

[2]Dr. Kiran Srivastava,Clinical Psychologist, Email: kiran_srivastava63@yahoo.com, Orcid ID: https://orcid.org/0000-0002-4312-1641

**Corresponding author: Dr. Lalit Kumar Singh (Llt_kumar@yahoo.com)*

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Abstract

Identifying maternal health risk early is critical to minimizing preventable complications, especially in low-resource and rural areas. In this study, machine-learning methods have been used to assess the capability of clinical and physiological parameters to classify the maternal health risk. We performed a secondary analysis of the Maternal Health Risk dataset with maternal age, SBP, DBP, blood sugar, body temperature and heart rate as predictors. One physiologically impossible heart-rate observation was eliminated, and 451 records remained after the elimination of exact duplicate records. The following machine learning supervised models were developed: multinomial logistic regression, decision tree, random forest, support vector machine, and gradient boosting. Model performance was evaluated based on the accuracy, balanced accuracy, precision, recall, macro F1-score, Cohen's kappa, receiver operating characteristic, Area under the curve, and confusion matrices. Gradient Boosting performed the best overall (74.7% accuracy, 66.0% balanced accuracy, macro F1 score of 67.3% and Cohen's kappa score of 0.557). For low-risk cases, the model had a high recall, and for high-risk cases, a good discrimination, with mid-risk cases being relatively poor. The most significant predictor was blood sugar, followed by SBP. Routinely collected indicators can be used with machine-learning models to provide preliminary maternal risk screening. But more general predictors and external validation are needed before clinical use.

Keywords: maternal health risk; machine learning; rural Bangladesh; Gradient Boosting; clinical indicators; physiological indicators; risk prediction

1. Introduction

Even though complications during pregnancy and childbirth remain a significant cause of preventable morbidity and mortality in women, maternal health continues to be a public health priority, especially in LMICs. While maternal mortality has dropped in recent decades, there has been an uneven rate of change, and many countries still have a high proportion of women with delays in diagnosis, referral and access to quality obstetric care (World Health Organization, 2023). In addition to clinical complications, structural factors like poverty, low level of education, limited decision-making authority and poor access to health services all play a part in shaping maternal mortality rates (Ahmed et al., 2010). Therefore, severe maternal morbidity is an important measure of health system performance because many women survive life-threatening complications and still have long-term physical, psychological and social impacts (Geller et al., 2018).

In rural and low-resource environments, women are less likely to attend antenatal services, have access to less skilled health care providers, may not have a strong referral process, and may have limited access to diagnostic technologies. While maternal health outcomes have improved in Bangladesh, the disparities between the urban and rural populations and among socioeconomic groups are particularly relevant to consider these challenges (Niport & ICF, 2020). In these settings, early detection and intervention for pregnancy complications will depend on easy-to-use screening strategies that can detect risk at an early stage and enable prompt intervention. (Goldenberg et al., 2018) The persistent global maternal mortality rates also suggest lack of effective implementation of strategies, particularly in terms of consistency and equity (Khalil et al., 2023). The need to assess the woman's pregnancy at regular intervals, detect any abnormality early and monitor the mother and baby properly during pregnancy has been highlighted in the international guidance (World Health Organization, 2022).

Some of the major factors that contribute to poor maternal outcomes are hypertensive disorders and metabolic complications. Pre-eclampsia is a multi-system pregnancy disorder characterised by hypertension, endothelial dysfunction, organ damage, foetal growth restriction and elevated maternal and foetal mortality and morbidity (Chappell et al., 2021). It has a vast pathophysiology, as well as a wide clinical spectrum, making it difficult to be recognized early, especially in areas with limited laboratory and specialized services (Rana et al., 2019). The monitoring of blood pressure, blood pressure risk categorisation, and early management for prevention of complications are recommended internationally (Magee et al., 2022). Adolescent pregnancy may also place greater risk because it has been demonstrated that there is a significant burden of preeclampsia and eclampsia in younger mothers (Macedo et al., 2020). In other parts of the world, direct obstetric complications such as hypertensive disorders, haemorrhage, infection, and other obstetric complications continue to be significant causes of maternal mortality (Say et al., 2014).

Another significant pregnancy condition is gestational diabetes mellitus, as the presence of gestational diabetes can increase the risk of complications in pregnancy such as hypertensive disorders, operative delivery, macrosomia, and long-term metabolic disease in both mother and child (Sweeting et al., 2022). Recent biological research also indicates an impact of EVs on intercellular communication and metabolic adaptation in gestational diabetes, further painting a complex picture of the pathways of maternal risk (Palma et al., 2022). The information of routine parameters, like maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature and heart rate, can therefore be valuable to obtain preliminary information for maternal risk evaluation, particularly in areas of less advanced investigations.

Machine learning can be a valuable tool for analysing these indicators as it can detect nonlinear relationships, interactions, and combinations of variables that can't be captured by traditional statistical methods. Machine-learning models have previously been proven to be able to predict pre-eclampsia and other pregnancy-related complications early (Marić et al., 2020). In addition, the systematic review has identified a growing application of AI in the prediction of pre-term birth and in other obstetric conditions, though the quality of the models, their generalisability and reporting are inconsistent (Akazawa & Hashimoto, 2022; Bertini et al., 2022). This research indicates that predictive modelling can assist clinical decisions, but that these models should be tested in accordance with suitable validation processes with clinically relevant performance metrics.

While there is increasing interest in the use of AI in maternal health, key gaps are identified. Numerous studies rely on very specific hospital information, are not easily interpretable, or lack reports of accuracy at the class level. This is difficult when it comes to maternal health, where not catching high-risk cases could have more severe consequences than identifying them as lower-risk cases. Comparable and transparent models which rely on indicators routinely available and evaluate their utility for the early identification of maternal risk in rural settings are therefore needed.

Hence, the present study aimed to develop and compare different machine learning-based maternal health-risk prediction models based on clinical and physiological indicators that are relevant to rural Bangladesh.

Study Objectives

- To assess the differences in clinical and physiological parameters between low-risk, mid-risk and high-risk maternal groups.
- Create and compare machine-learning classifiers for maternal health risk classification.
- To pinpoint the most salient indicators that help to predict maternal risk.

2. Materials and Methods

2.1 Research Design

The research in this study used a quantitative, retrospective and secondary data design to predict the levels of risk for maternal health through machine-learning methods. The outcome variable was divided into three classes: low risk, mid risk and high risk, so a supervised multiclass classification approach was used. The objective of this study was to find out whether routine clinical and physiological measures can aid in early maternal risk assessment in rural Bangladesh.

2.2 Dataset Source and Study Variables

The publicly available Maternal Health Risk data was used, which was based on 1014 maternal health observations in rural Bangladesh. Six predictor variables are given: maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and heart rate. The dependent variable is RiskLevel, which is a classification of each observation as low, mid, or high maternal risk. The following table shows the number of low-risk, mid-risk and high-risk observations in the original data set.

2.3 Data Screening and Cleaning

The data set was checked for missing data, duplicate data, inconsistent data labels, physiologically implausible data, and outliers (Ahmed, 2020). There were no missing values found. To minimize the risk of information leakage and high model performance, however, 562 exact duplicate records were found and removed from the primary analysis. A value of 7 bpm was excluded as being clinically implausible. Extreme but potentially valid clinical measurements were kept as they could be true high-risk maternal conditions.

2.4 Data Preprocessing

All target categories were coded numerically as low risk, mid risk, and high risk for analysis in a computer. The predictors were all quantitative, and categorical transformations were not necessary. The mean and standard deviation of the training data were used to standardise all the scale-sensitive models: multinomial logistic regression and support vector machine. The original scales of the measurements were used to train tree-based algorithms. To avoid the data leakage problem, all the data preprocessing procedures were done after partitioning the data.

2.5 Exploratory and Statistical Analysis

Each predictor was described using descriptive statistics: mean, standard deviation, median, interquartile range, minimum and maximum. Frequencies and percentages were used to describe the maternal risk categories. Data distributions and correlations among variables were analyzed using histograms and boxplots. The clinical indicators were analysed for differences between the three risk groups using one-way analysis of variance, where the distribution of data was normal, and the Kruskal–Wallis test where the distribution of data was not normal. The level of significance was chosen as ($p<0.05$).

2.6 Data Partitioning and Validation

After the data had been cleaned, the data were split into 80% (training) and 20% (testing), and the ratio of each maternal risk group was maintained. The model was developed, the hyperparameters were optimized and the models were cross-validated using the training data set and the testing data set was kept to evaluate the final performance of the models. Five-fold Cross-Validation was used to ensure consistent estimation of model performance. To minimise information leakage, records having the same clinical profile were grouped into the same partition.

2.7 Machine-Learning Model Development

Five machine-learning-based models were created and evaluated: multinomial logistic regression, decision tree, Random Forest, support vector machine and gradient boosting. Logistic regression was used as a baseline model that was considered interpretable and decision tree and Random Forest models were utilized to capture nonlinear relationships and interactions among the predictors. To overcome the limitations of logistic regression, two other approaches support vector machine and advanced ensemble-learning method, gradient boosting, were added to identify complex decision boundaries.

2.8 Model Evaluation and Interpretation

The accuracy, balanced accuracy, precision, recall, specificity, macro-averaged F1-score, weighted F1-score, Cohen's kappa, multiclass ROC-AUC, and confusion matrices were used to evaluate model performance. The increased attention to recall was given to the high-risk group, as the lack of identification of high-risk maternal cases can lead to significant clinical consequences. The model with the best performance was explained by permutation feature importance and SHAP analysis to determine the most important variables for maternal risk classification.

2.9 Sensitivity Analysis and Ethics

For both the original dataset and the deduplicated dataset, sensitivity analyses were conducted with the results of the cleaned dataset (based on dropping implausible measurements). A comparison of models with and without class weighting was also made to evaluate the impact of the moderate class imbalance. No direct contact or intervention with participants was made as the study was a secondary anonymised public study with no personally identifiable information being present.

3. Results

3.1 Data Screening and Final Analytical Sample

There were 1014 observations, 6 predictor variables and one multiclass outcome variable in the original Maternal Health Risk dataset. There were no missing values detected. But 562 exact duplicate observations were found, accounting for 55.42% of the original observations. To avoid having duplicate observations in both the training set and the testing set, these

duplicate observations were removed. There was one other unique record that was omitted because the heart rate value was physiologically implausible (7 bpm). This resulted in 451 observations being kept for primary analysis is shown in Table 1.
After cleaning the data, there were 233 low-risk, 106 mid-risk, and 112 high-risk cases. The percentages of low, mid, and high-risk observations were 51.66%, 23.50%, and 24.83%, respectively. The maternal risk categories are presented as a distribution in Figure 1.

Table 1. Data Screening and Composition of the Final Analytical Sample

Data-screening stage	**Records, n**	**Percentage of the original dataset**
Original dataset	1,014	100.00
Exact duplicate records identified	562	55.42
Unique records after duplicate removal	452	44.58
An implausible heart-rate record was excluded	1	0.10
Final analytical sample	451	44.48
Low-risk cases	233	51.66*
Mid-risk cases	106	23.50*
High-risk cases	112	24.83*

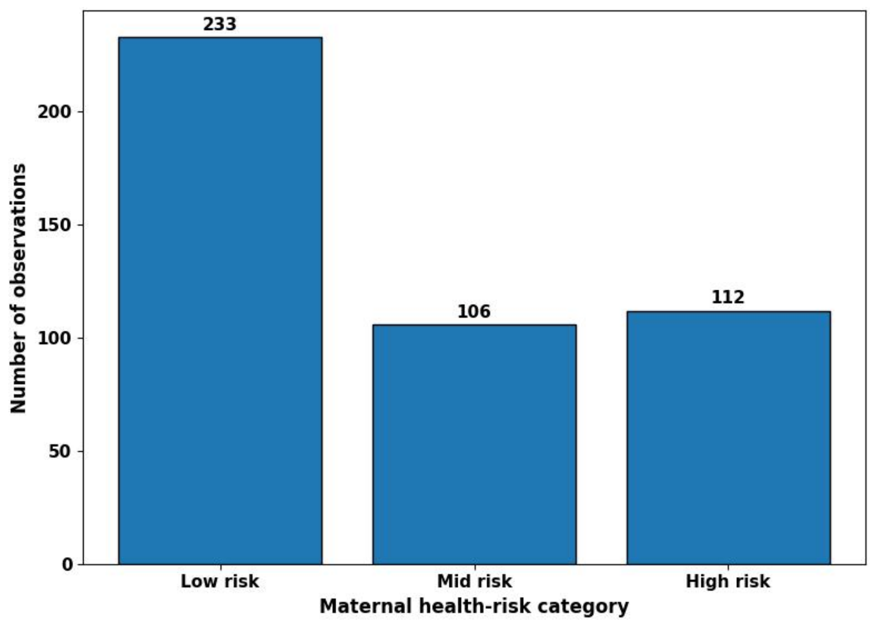

Figure 1. Distribution of maternal health-risk categories in the cleaned dataset

3.2 Descriptive Characteristics of Maternal Health Indicators

Table 2 shows the descriptive characteristics of the maternal health indicators by the three risk groups. The mean age of high-risk women (33.73 years) was significantly older than that of mid-risk women (28.54 years) and low-risk women (27.37 years). The mean systolic blood pressure was higher in each of the three categories; low risk, 105.37 mmHg; mid-risk, 112.41 mmHg; and high risk, 119.49 mmHg.
The same trend could be seen with the diastolic blood pressure: 72.72 mmHg in low-risk cases and 81.54 mmHg in high-risk cases. Blood sugar was the best discriminator for the risk categories. The mean blood sugar level was 7.20 mmol/L in the low-risk category, 7.89 mmol/L in the mid-risk category, and 11.17 mmol/L in the high-risk category. There was also moderately higher body temperature and heart rate values for the high-risk cases. Figure 2 illustrates the distribution of each of the six indicators by the three categories of maternal risk.

Table 2. Clinical and Physiological Indicators Across Maternal Risk Categories

Indicator	Low risk, mean ± SD	Mid risk, mean ± SD	High risk, mean ± SD
Age, years	27.37 ± 13.89	28.54 ± 12.72	33.73 ± 13.57
Systolic blood pressure, mmHg	105.37 ± 15.51	112.41 ± 15.06	119.49 ± 20.97
Diastolic blood pressure, mmHg	72.72 ± 13.11	74.89 ± 12.17	81.54 ± 14.70
Blood sugar, mmol/L	7.20 ± 0.57	7.89 ± 2.38	11.17 ± 3.94
Body temperature, °F	98.36 ± 1.11	98.86 ± 1.47	99.23 ± 1.71
Heart rate, beats/minute	73.04 ± 7.02	73.90 ± 7.00	76.48 ± 8.50

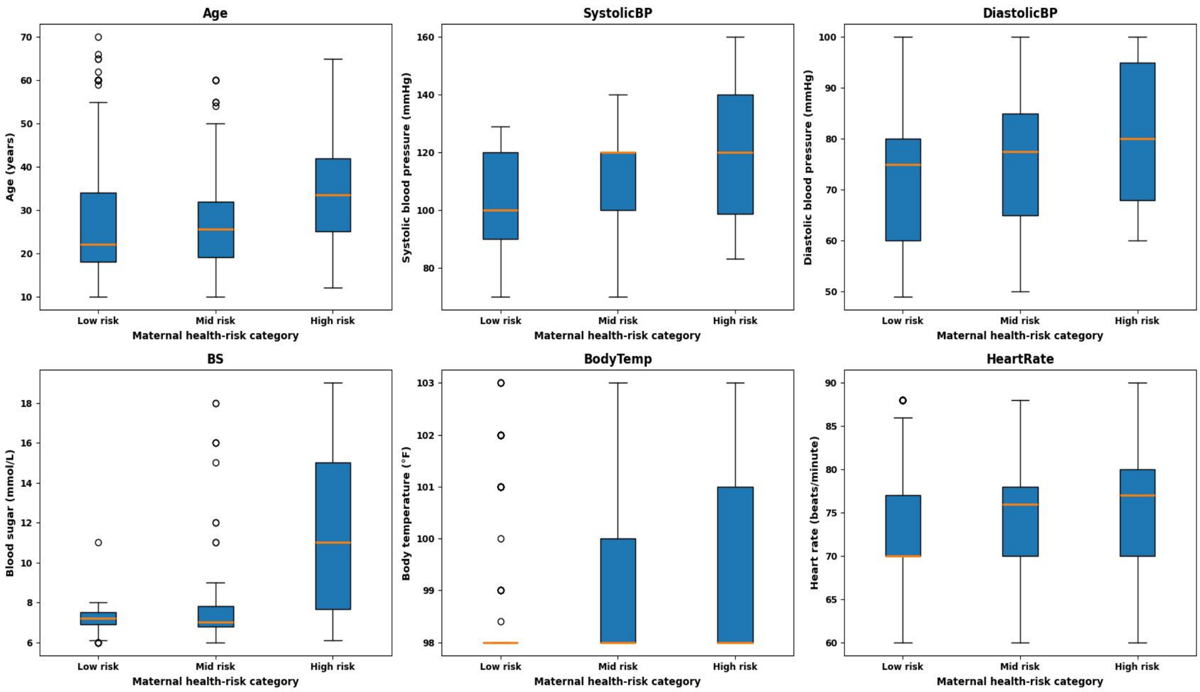

Figure 2. Distribution of clinical and physiological indicators across maternal risk categories

3.3 Differences in Indicators Across Maternal Risk Categories

Table 3 shows that each of the 6 predictors was significantly different among the categories of maternal risk. The Kruskal–Walli's statistic and the epsilon-squared effect size of blood sugar were the highest of the risk groups at 106.65 and 0.234, respectively. This suggested that blood sugar was most strongly correlated with maternal risk classification in univariate analysis. Systolic blood pressure had the second highest effect (H=44.78), (p<0.001), with an epsilon-squared value of 0.096. Other interesting differences were seen in body temperature, diastolic blood pressure, age, and heart rate. Heart rate had the smallest effect size but was still significantly different. The relationships among the clinical and physiological parameters are shown in Figure 3.

Table 3. Comparison of Maternal Health Indicators Across Risk Categories

Indicator	Kruskal–Wallis H	p-value	Epsilon-squared
Age	23.16	<0.001	0.047
Systolic blood pressure	44.78	<0.001	0.096

Diastolic blood pressure	25.54	<0.001	0.053
Blood sugar	106.65	<0.001	0.234
Body temperature	31.90	<0.001	0.067
Heart rate	14.44	0.001	0.028

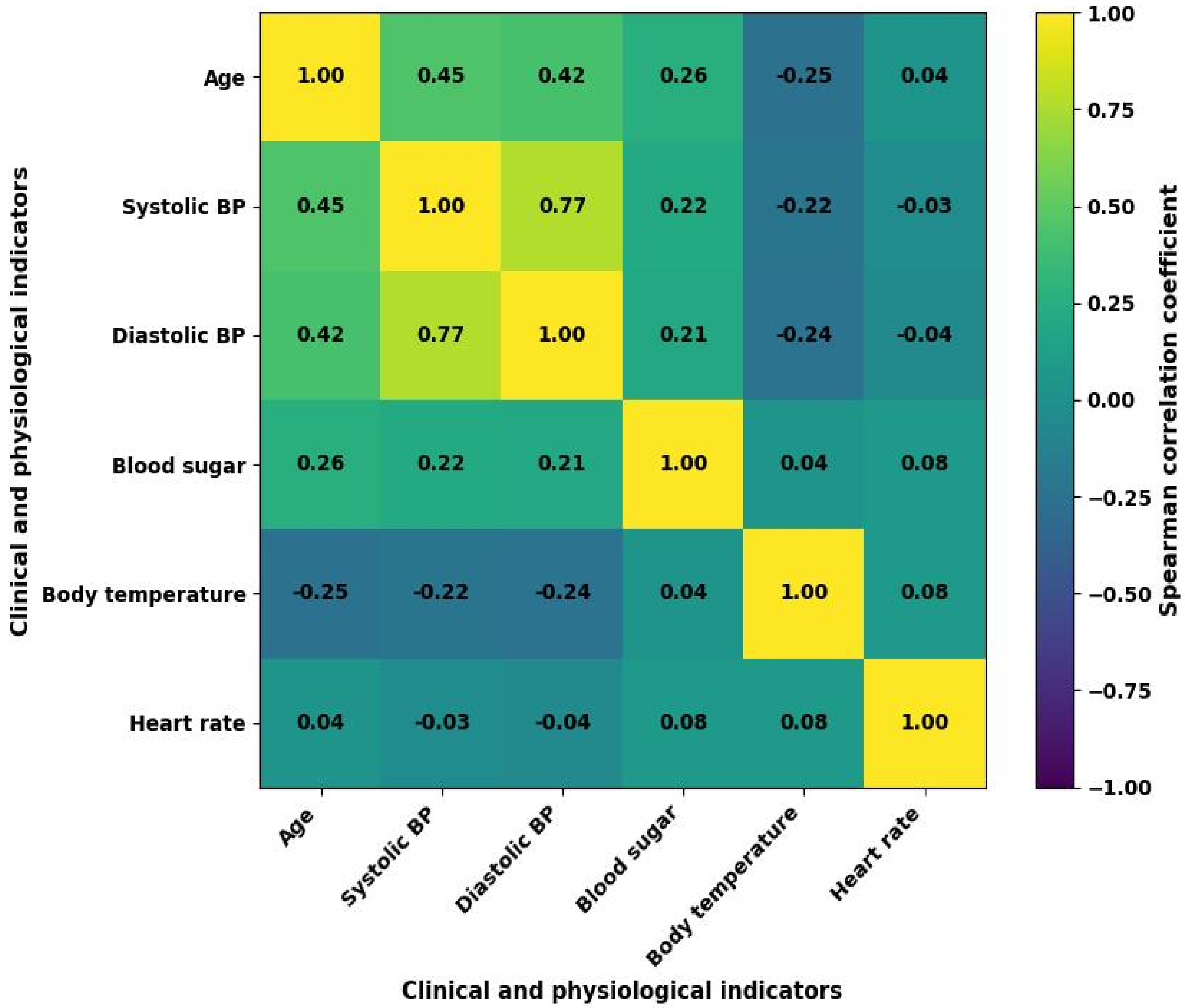

Figure 3. Correlation matrix of maternal clinical and physiological indicators

3.4 Machine-Learning Model Performance

Data was split into 360 training observations and 91 independent testing observations with an 80:20 stratified and clinical-profile-aware data split. There were 47 observations in the testing data set with low risk, 22 with medium risk, and 22 with high risk. The training set was cross-validated five times. As shown in Table 4, Gradient Boosting gained the best test accuracy (74.73%) with independent data, while Random Forest obtained 71.43%. The best mean cross-validated macro F1 score was achieved by the Decision Tree with 64.19%, but when tested independently, the score dropped to 58.34%, signifying poorer generalisation. The test accuracy of Logistic Regression was found to be the lowest of the models evaluated. The model accuracy, balanced accuracy, and macro F1-score are graphically compared in Figure 4.

Table 4. Comparative Performance of the Machine-Learning Models

Model	CV macro F1, mean ± SD	Accuracy	Balanced accuracy	Macro precision	Macro recall	Macro F1	Weighted F1	Cohen's kappa
Logistic Regression	0.564 ± 0.032	0.637	0.589	0.595	0.589	0.591	0.633	0.403
Decision Tree	0.642 ± 0.051	0.670	0.578	0.607	0.578	0.583	0.648	0.435
Random Forest	0.612 ± 0.029	0.714	0.630	0.686	0.630	0.645	0.696	0.507
Support Vector Machine	0.612 ± 0.031	0.670	0.586	0.615	0.586	0.594	0.655	0.440
Gradient Boosting	0.622 ± 0.014	0.747	0.660	0.737	0.660	0.673	0.720	0.557

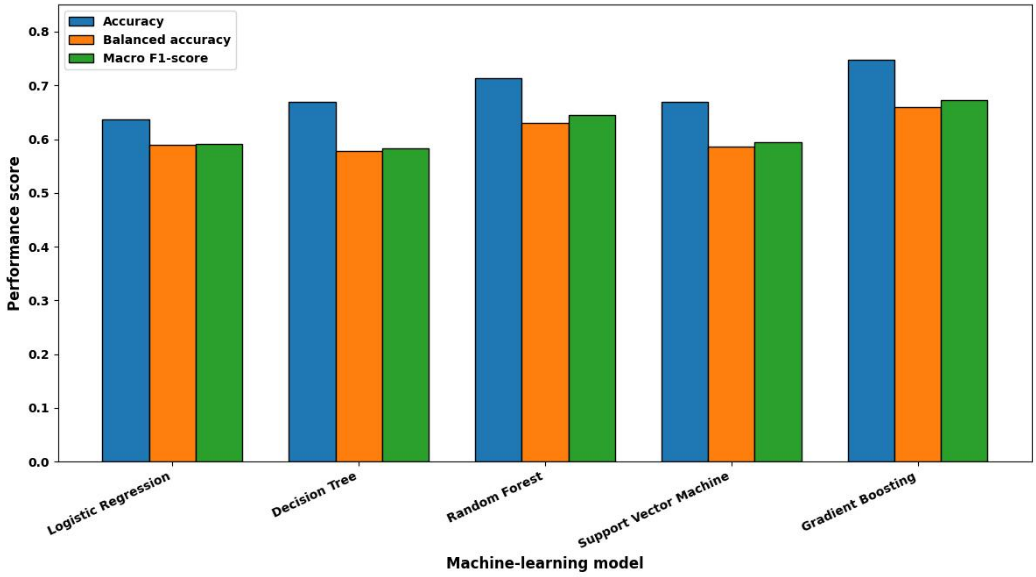

Figure 4. Comparative predictive performance of the machine-learning models

3.5 Classification Performance of the Best Model

Figure 5 shows the confusion matrix of the Gradient Boosting model. There were 47 low risk cases, with 46 correctly classified and 1 incorrectly classified as mid-risk. Of the 22 mid-risk cases, seven were correctly identified, 12 were incorrectly identified as low-risk, and three were identified as high-risk. There were 22 high-risk cases of which 15 were correctly identified, 3 were classified as "mid risk" and 4 as "low risk. The results from the classes are reported in Table 5. A model with the highest recall value was the low-risk model with a value of 97.87%.

Table 5. Class-Specific Performance of the Gradient Boosting Model

Risk category	Precision	Recall	Specificity	F1-score	Test cases, n
Low risk	0.742	0.979	0.636	0.844	47
Mid risk	0.636	0.318	0.942	0.424	22
High risk	0.833	0.682	0.957	0.750	22

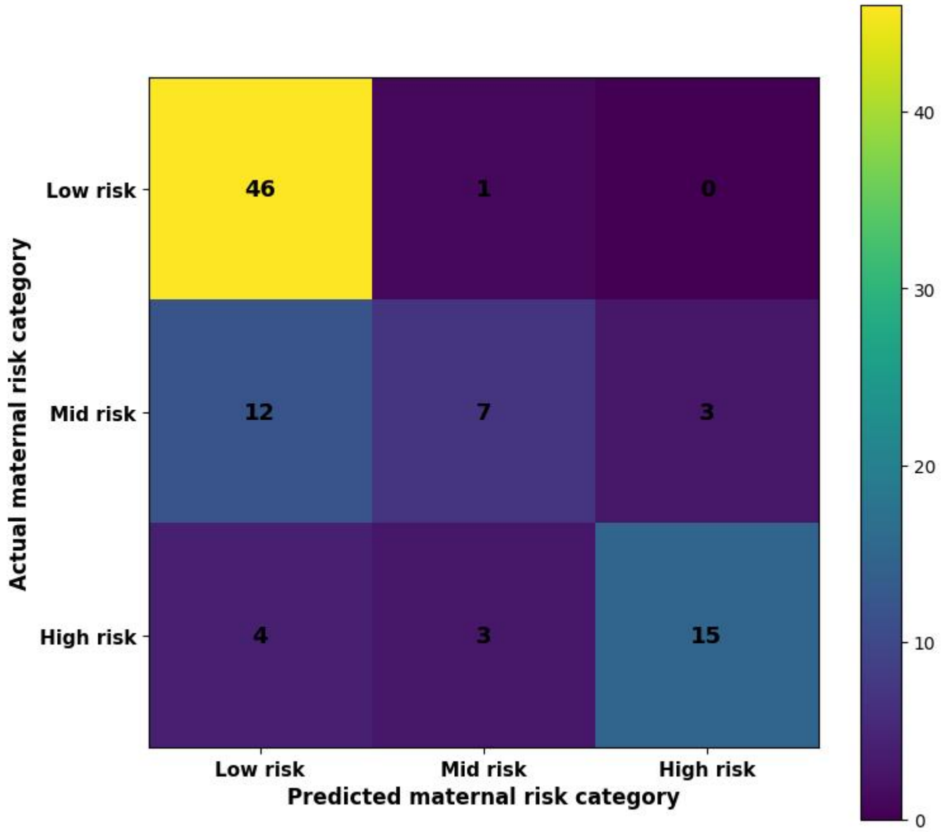

Figure 5. Confusion matrix of the Gradient Boosting model

3.6 Receiver Operating Characteristic Analysis

The one versus rest (1-vs-all) receiver operating characteristic (ROC) curves for Gradient Boosting are shown in Figure 6. The overall macro average ROC-AUC for the model was 0.798. The highest class-specific discrimination was achieved for the high-risk class (AUC- 0.884). The low-risk and mid-risk categories had AUC values of 0.839 and 0.671, respectively.

The results show that the model was successful in discriminating between high-risk and the rest of the groups.

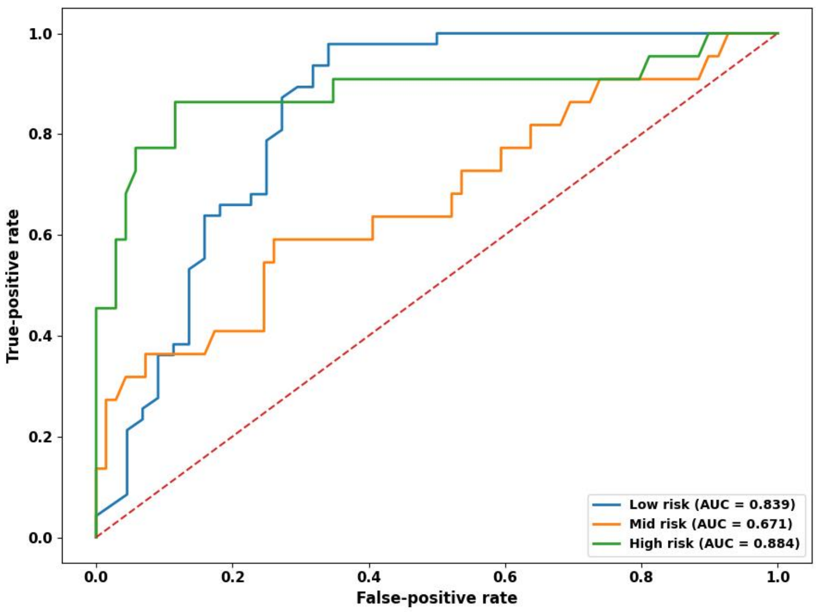

Figure 6. One-versus-rest ROC curves for the Gradient Boosting model

3.7 Predictor Importance

We used permutation feature importance to assess the importance of the clinical and physiological variables for the macro-F1 score of the Gradient Boosting model. Table 6 and Figure 7 indicate that blood sugar was the most influential predictor with a mean permutation importance of 0.220. The second most important variable was systolic blood pressure with a mean importance of 0.088.

Table 6. Permutation Importance of Maternal Health-Risk Predictors

Rank	Predictor	Mean importance	Standard deviation
1	Blood sugar	0.220	0.042
2	Systolic blood pressure	0.088	0.024
3	Body temperature	0.024	0.027
4	Heart rate	0.008	0.012
5	Age	0.003	0.013
6	Diastolic blood pressure	−0.011	0.017

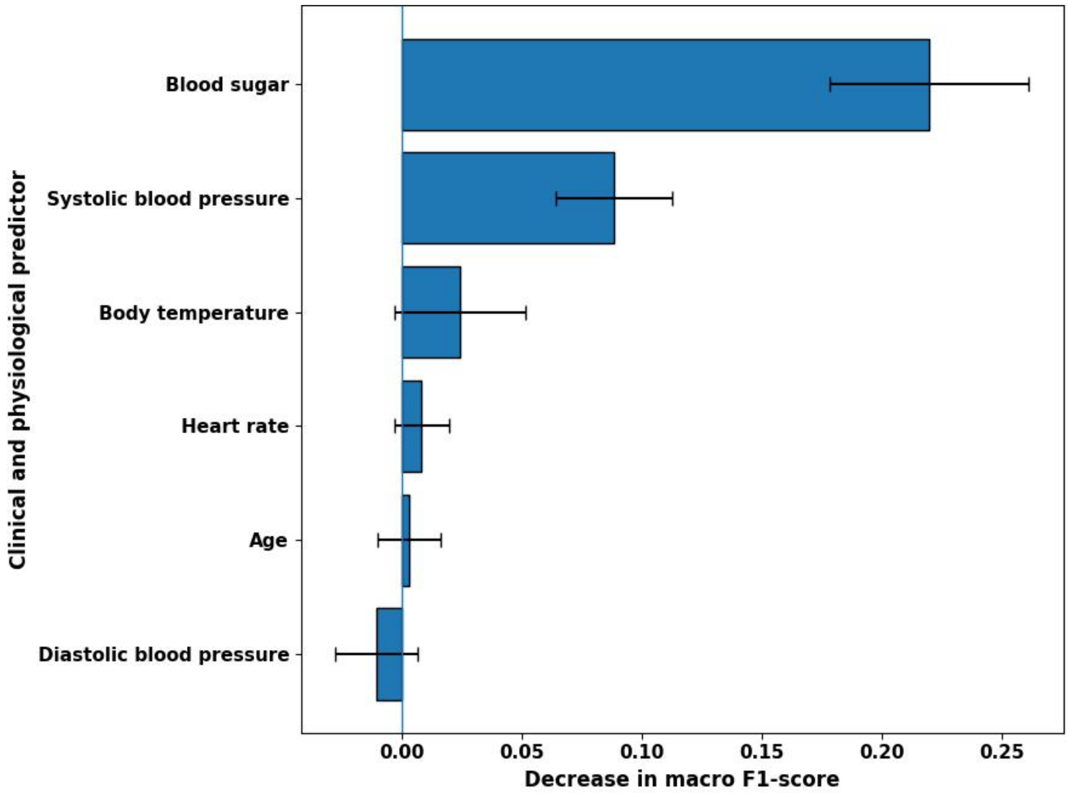

Figure 7. Permutation importance of maternal health-risk predictors

Overall, the results showed that machine-learning algorithms were able to moderate predict maternal health-risk levels with six routinely measured indicators. Gradient Boosting had the best overall performance in the tests, especially in detecting low-risk and high-risk cases. However, the poor overall identification of mid-risk cases suggested the present clinical and physiological parameters were inadequate to fully differentiate the mid-risk group.

4. Discussion

The present study compared the classification of maternal health risk by five machine-learning models, both clinical and physiological. Gradient Boosting demonstrated the best overall performance in the task, with an accuracy of 74.7%, a balanced accuracy of 66.0%, a macro F1 Score of 67.3% and a Cohen's kappa of 0.557. Random Forest obtained the best performance overall, and Logistic Regression had relatively poor discrimination. The results showed that nonlinear ensemble models outperformed the traditional linear classification models in the identification of the nonlinear relationship between maternal age, blood pressure, blood sugar, body temperature and heart rate.

Blood sugar levels were the most significant predictor in both the univariate analysis and the machine learning analysis. Blood sugar gave the largest effect size across the three levels of risk and those high-risk observations were significantly higher in mean blood sugar than those in low and mid risk. This finding is clinically feasible because there are maternal metabolic abnormalities that overlap with hypertensive and cardiovascular abnormalities in pregnant women with abnormal glucose regulation. In people with limited access to health education (Abdulghani et al., 2021).

Second most influential was systolic blood pressure, with a weaker independent contribution after the effects of the other variables were taken into account; diastolic blood pressure was the third most influential. This discovery could be attributed to the information that is common to both systolic and diastolic readings. Keeping the blood pressure marker prominent was in keeping with the known importance of hypertension in the cause of severe maternal morbidity. Preventive strategies include early identification of women at high risk for pre-eclampsia and the use of low-dose aspirin in eligible pregnancies, which have been recommended to help lower morbidity and mortality associated with pre-eclampsia (US Preventive Services Task Force et al., 2021). The importance of the systolic blood pressure therefore, supports the clinical significance of routine antenatal blood-pressure monitoring.

The Gradient Boosting model had the highest precision (83.3%) for high-risk cases and a good clinical discrimination (AUCROC=0.884) for high-risk cases, and the highest recall (97.9%) for low-risk cases. However, only 31.8% of the mid-risk observations were correctly identified by the model. This means that there is significant overlap between the intermediate risk group and the low and high risk groups. This limited set of predictors might not be complete in accounting for socioeconomic factors, past obstetric history, gestational age, access to care, or underlying comorbidities. SDOH and racial/ethnic differences are risk factors that do not always correlate with routine physiological measurements, meaning that more comprehensive risk models should include contextual factors as much as possible (Garringer, 2024).

The results also highlight the need to consider the various indicators of performance instead of just accuracy. In the maternal health context, the misclassification of low-risk cases is less of a problem than the failure to classify high-risk cases. Artificial intelligence-based clinical prediction research (AI-CPR) reporting guidelines have been recommended by the current reporting guidelines (Collins et al., 2024) to include clear summaries of data preparation, predictor selection, model development, model validation, and class-specific performance. The present study has followed this principle and reported: Balanced accuracy, macro-averaged measures, class-specific recall, confusion matrices and receiver operating characteristic analysis.

While feature importance analysis enhances the transparency of the model, explainability does not necessarily imply clinical validity. Some explainable AI approaches could give the impression of making sense of things, but not show bias, instability or causal relationships (Ghassemi et al., 2021). Therefore, the role of blood sugar and systolic blood pressure should be considered as predictive and not causal. Artificial intelligence in biological and clinical studies should be combined with physiological insights, clinical knowledge, and ethical considerations, as responsible use is essential for computational findings to complement physiological knowledge and clinical expertise (Mohanan, 2025).

This study has a number of limitations. Over half of the original observations were exact duplicates, and the removal of these observations significantly reduced analytical sample. Some of the variables that were not included in the model (parity, gestational age, previous complications, haemoglobin, body mass index and antenatal attendance) could have affected the performance of the model. (Liu et al., 2020; Rivera et al., 2020).
In spite of such constraints, the findings of this study indicate the feasibility of using simple indicators that can be routinely measured to classify maternal risk in resource-limited areas. These models could be helpful for frontline health workers to prioritise referrals but cannot supplant the individual professional judgement. In addition, lessons learned from maternal mortality and morbidity reviews highlight the need to integrate risk prediction with timely escalation and coordination of care, as well as effective clinical response, to achieve better outcomes (Knight, 2021).

5. Conclusion

The present study showed that clinical and physiological factors, which are normally measured, can be used to predict maternal health risk to a medium degree of prediction. Gradient Boosting had the best overall performance of the five machine learning models tested, as it had the least error rate, highest balanced accuracy, macro F1 score, and Cohen's kappa. The model predicted low-risk and high-risk cases well, but not so well the mid-risk cases. Blood sugar showed the greatest effect, followed by systolic blood pressure, with body temperature, heart rate, age and diastolic blood pressure having lesser effects. The results suggest that nonlinear ensemble models are more appropriate than the traditional linear models for modelling complex relationships between maternal health indicators. But findings must be taken with a pinch of salt as there were many duplicate records in the dataset, and not all predictors were included. There were no data for important obstetric, socioeconomic, and healthcare-access factors, which could have limited the ability of the model to identify intermediate-risk pregnancies. However, the study underscores the value of machine-learning tools in screening in rural and resource-limited areas. These tools can help front-line health workers to prioritize maternal referrals and identify mothers who need more intensive surveillance. The model must not be used instead of clinical judgment, however. There is a need for external validation with larger, more diverse and prospectively collected datasets before practical implementation in maternal health care systems.

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