

Machine learning approach to evaluate the significance of clinical factors and laboratory markers in predicting postpartum hemorrhage

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Abstract

Background

Identifying risk factors is the crucial step in preventing postpartum hemorrhage (PPH). Integrating laboratory, demographic, and real-time intrapartum data into predictive models allows clinical teams to move from broad risk categories to specific, individualized risk probabilities. This research aimed to evaluate the predictive power of machine learning (ML) in PPH.

Methods

This prospective cohort study took place at two tertiary hospitals in Tehran, Iran, between November 2024-October 2025. Inclusion criteria required singleton pregnancies reaching 28 weeks of gestation, agreement to join the study, and complete data without any omissions. Those with chorioamnionitis, or who received blood transfusions during the antepartum period were excluded. Patients were divided into those with PPH and those without PPH. Maternal clinical and laboratory data were established as input for ML models. A variety of algorithms were used to evaluate the power of ML models in predicting PPH. Accuracy, sensitivity, specificity, precision, F1 Score, Receiver Operating Characteristic - Area Under the Curve (ROC-AUC), and Brier score were utilized to assess the performance of ML models.

Results

Among the 604 eligible participants, 55 (9.10%) experienced PPH. Significant variations were observed in serum lactate levels between PPH and non-PPH instances. Preeclampsia and gestational age were associated with PPH. PPH was less common in preterm deliveries and those with previous cesarean sections. Evaluating the performance of ML models for predicting PPH showed that the Logistic Regression model exceeded the performance of the others, achieving an average ROC-AUC of 0.71 and a Brier score of 0.07; however, additional metrics (sensitivity: 0.02, precision: 0.10, F1Score: 0.04) suggested it was inadequate in effectively predicting PPH.

Conclusions

The Pearson correlation showed a strong positive relationship among serum lactate levels, gestational age, history of cesarean, and preeclampsia related to PPH; however, the predictive performance of the ML models for PPH was poor.

Background

Postpartum hemorrhage (PPH) is the foremost cause of maternal death globally, conventionally characterized as a blood loss of ≥ 500 mL following vaginal delivery or ≥ 1000 mL post-cesarean section within 24 hours after childbirth [1]. Nevertheless, modern clinical definitions, such as those by ACOG, characterize PPH as a total blood loss of $\geq 1,000$ mL with signs or symptoms of hypovolemia occurring within 24 hours postpartum, irrespective of the delivery method [2].

PPH is believed to affect around 10% of global births, translating to approximately 27 million women annually [3]. Combined epidemiological data indicates a pooled prevalence of 12.6% for vaginal deliveries and a notably higher 30.9% for cesarean births [4]. PPH is the primary direct reason for maternal fatalities globally. It represents more than 20% of worldwide maternal deaths, claiming about 43,000 lives each year—which equates to around one death every 12 minutes. Over 80% of these deaths take place in sub-Saharan Africa and South Asia [5]. In Iran, national data reveals that standard PPH complicates around 10.8% of deliveries, closely aligning with the global average baseline of 10% [6]. The WHO does not have a consolidated, nationwide incidence rate specifically for PPH in Iran. Instead, WHO assesses the wider measure of Maternal Mortality Ratio (MMR). Nonetheless, according to research supported by Iran and the WHO, PPH is officially recognized as the primary direct cause of maternal mortality in Iran, constituting approximately 23% – 43% of all maternal fatalities [7]. Data released by the World Health Organization (WHO) and related global burden metrics indicate that the incidence of PPH is notably consistent worldwide; however, survival rates fluctuate significantly based on the medical resources available in each country.

Recognizing risk factors during the antepartum and intrapartum stages is the essential initial step in avoiding PPH. As many of PPH instances can be predicted and reduced by implementing systematic screening. This enables clinical teams to shift from emergency response to proactive, preventative treatment [8]. Screening for clinical risk factors is vital, but predicting PPH with quantitative models changes subjective clinical concerns into accurate, numerical risk evaluations. By incorporating laboratory, demographic, and real-time intrapartum data into predictive models, clinical teams can transition from general risk classifications to precise, personalized risk probabilities [9]. This transition enables focused, premium preventative actions prior to blood loss surpassing safe levels [10]. Accurate PPH predicting depends on integrating various specific types of patient information. The strongest algorithms combine hemostatic biomarkers, uterine physical measurements, and maternal attributes. [11, 12].

Traditional methods used for predicting PPH depend on set mathematical rules, whereas artificial intelligence (AI) models reveal concealed data patterns directly from extensive datasets. In contrast to conventional scoring systems that examine risk factors separately, ML models employ algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting to interpret intricate Electronic Health Record (EHR) data. This enables them to reveal concealed risk patterns prior to delivery [13]. AI-powered machine learning (ML) models greatly exceed traditional statistical techniques in predicting PPH, mainly because of their capacity to analyze dynamic, non-linear interactions in real time [14–20]. This study focused on assessing machine learning's predictive ability in PPH through demographic information, prenatal and antenatal factors, as well as biomarkers and lab indicators.

ML-based models predict PPH by identifying non-linear interactions among clinical variables, frequently revealing maternal age, pre-delivery hemoglobin/hematocrit levels, hypertensive disorders, and body mass index (BMI) as the most heavily weighted predictive factors [21]. Global ML-driven systematic reviews and predictive modeling research categorize the main weighted factors (or "features") into four unique phases of the maternal timeline including 1) antenatal & demographic factors, 2) labor & delivery characteristics, 3) fetal & placental features, 4) biomarkers & laboratory indicators [13, 21].

Most published ML models for PPH are static solely on antepartum models. They depend on information available prior to admission (e.g., age, BMI, history). Models that include intrapartum data typically consider labor as one moment in time. However, in our study we aimed to center on multiple attributes integrating all four characteristics outlined earlier derived from prior research.

The majority of PPH ML-based research is made up of single-center investigations conducted on uniform populations in affluent Western nations or particular localized networks. Due to significant variations in baseline risks among regions (e.g., Iran's C-section rate exceeding 50% compared to Western Europe's emphasis on vaginal deliveries [22, 23]), these models experience considerable overfitting and show inadequate performance when utilized in different healthcare systems. Our study can address this void by creating a model specifically designed and verified using regional data groups that inherently consider unique local healthcare systems, documentation practices, and distribution patterns.

Methods

Study design

This prospective cohort study took place at two tertiary hospitals in Tehran (Shahid Akarabadi hospital and Firoozgar Hospital) between November 2024 and October 2025. This research adhered to the Declaration of Helsinki and was conducted following ethics committee authorization. The Research and Ethics Committee of the Iran University of Medical Sciences authorized the study (IR.IUMS.REC 1403.1140). The data of all patients who gave written informed consent for research use were examined. For individuals below eighteen years old, consent was obtained from their guardians. Statistical analysis was conducted with patient confidentiality in accordance with ethics committee guidelines. The TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis) was used to report the findings [24]. Supplementary file 1

Study population

The study population included all expectant mothers admitted to these two facilities for delivery during the research timeframe. Inclusion criteria required a singleton pregnancies reaching at least 28 weeks of gestation, agreement to join the study, and complete data without any omissions. Individuals diagnosed with chorioamnionitis, or who received blood transfusions during the antepartum period were excluded. Patients were first divided into two categories: those with PPH and those without PPH, to discern differences between the groups through univariate analysis. Then, the initial group was divided into four subgroups according to the severity of PPH [2].

Sample size

Standard statistical models like logistic regression require a minimum of 10 to 20 Events Per Parameter (EPP). However, methodological reviews show that ML algorithms require at least 20 EPP—and sometimes up to 50 or 200 EPP—to avoid overfitting and unstable performance metrics [14, 22]. Using a standard machine learning safety benchmark of 20 EPP, we calculate the required number of PPH events first: Required events (E) = $P \times EPP$

$$E = 30 \times 20 = 600 \text{ Cases}$$

Data collection

All women admitted for delivery in the two mentioned hospitals were evaluated for eligibility. Individuals who fulfilled the inclusion criteria were designated as participants in the study. Medical records were utilized to gather

data, including demographic details, individual and family medical histories, and obstetric background. All participants were observed to track birth results and complications. The main outcome was PPH defined as a total blood loss of $\geq 1,000$ mL with signs or symptoms of hypovolemia occurring within 24 hours postpartum, irrespective of the delivery method [2].

Handling missing data

In the evaluation of absent values, it was found that almost all variables were intact, with missing values appearing in just two columns. The "Gestational Hypertension" column had 7 missing entries, whereas the "Serum lactate level" column had 1. These values were specified to prevent the exclusion of samples. For "Gestational Hypertension," an additional column titled "Gestational hypertension_missing" was initially established to pinpoint samples with absent data in this variable; subsequently, the missing values were substituted with the mode of the column. In the same way, an auxiliary column titled "Serum lactate level_missing" was generated for "Serum lactate level," and the missing value was substituted with the median of the variable. After this step, there were no remaining missing values in the dataset.

Feature selection

In prominent studies assessing global hospital delivery registries, the following variables frequently score the highest in feature importance: Maternal characteristics and baseline health, laboratory biomarkers, pregnancy and placental issues, delivery and intrapartum factors [14, 21]. In our research, drawing from key predictors identified in earlier studies [14, 21], we chose maternal age, body mass index (BMI), smoking habits, substance use, gestational age, number of pregnancies, parity, abortions, history of cesarean sections, medical history, method of delivery, and laboratory tests (pre-delivery hemoglobin, serum lactate, and fibrinogen levels) as potential predictors for executing the ML models.

Development, calibration, and validation of ML models

The target variable, PPH, was initially segregated from the other features. The data was split into two segments, training and testing, with an 80/20 ratio; thus, 80% of the data was utilized for training the model and 20% for the preliminary assessment of the model's performance. Considering the inequality in the PPH outcome, the data was split in a stratified way to preserve the proportion of PPH and non-PPH samples in the training and testing datasets. A processing pipeline was created to get the data ready. In this pipeline, numerical variables underwent median imputation to address missing values and were subsequently standardized using StandardScaler. Categorical variables were formatted for model input through constant imputation followed by One-Hot Encoding. This enabled all preprocessing activities to be executed methodically and solely on the training data, minimizing the chance of data leakage.

A variety of ML algorithms were evaluated for performance comparison in predicting PPH, such as XGBoost, LightGBM, CatBoost, Random Forest, Decision Tree, AdaBoost, Logistic Regression, Linear support vector machine (SVM), Radial Basis Function Support Vector Machine (RBF SVM), Naive Bayes, k-nearest neighbors (KNN), and Neural Network. A distinct pipeline incorporating preprocessing and the model was created for each model to ensure that all models were trained using the same and comparable input format.

In the first implementation, the XGBoost model was trained on the training data and then assessed using the test data. Preliminary metrics, such as accuracy and ROC-AUC, were computed. Nevertheless, considering that the dataset is skewed concerning the primary outcome—with merely around 9.1% of samples in the PPH group—accuracy by itself is not an appropriate measure for evaluating the model. Consequently, in later phases, the effectiveness of all models will be evaluated with more extensive metrics including ROC-AUC, PR-AUC, Brier score, confusion matrix, sensitivity, and specificity, along with 10-fold cross-validation.

To evaluate model performance more consistently, 10-fold stratified cross-validation was applied to the training set, alongside the initial data split into training and testing. This approach involved dividing the training data into 10 segments, utilizing 9 segments for model training and 1 segment for validation in each iteration. Employing stratified cross-validation maintained the proportion of PPH and non-PPH samples in each fold to be as close as possible to the overall data distribution.

In every fold, the procedure for each model was trained individually. This matters since all preprocessing procedures, such as imputation, scaling, and one-hot encoding, were conducted solely on the training data of the specific fold and subsequently applied to the validation part of that fold. Consequently, the models were assessed without any information transfer from validation to training.

For every model and at each fold, the predicted likelihood for the PPH class was computed. Subsequently, a final predicted label was established using a standard threshold of 0.5. Subsequently, different performance metrics such as accuracy, ROC-AUC, PR-AUC, Brier score, and Confusion Matrix were computed. Additionally, the true outcome values and estimated probabilities for each fold were recorded to enable the plotting of ROC and Precision-Recall curves for the models in the subsequent stages.

Given the dataset imbalance and the small percentage of PPH patients, the interpretation of the results prioritized factors beyond just accuracy. Metrics like ROC-AUC and especially PR-AUC are crucial for assessing the model's ability to identify the positive class. Brier score was utilized to evaluate the quality of the probabilities forecasted by the models.

Evaluation metrics for the ML models performance

Accuracy, sensitivity, specificity, precision, F1 Score, Receiver Operating Characteristic - Area Under the Curve (ROC-AUC), Precision-Recall - Area Under the Curve (PR-AUC), and Brier score were utilized to assess the performance of ML models.

Accuracy refers to the ratio of the correct predictions made by a model compared to the overall number of predictions. This metric works well for balanced datasets, but in cases of class imbalance, accuracy might not reflect the true performance of the model. In these circumstances, additional metrics like precision and recall can offer a more accurate assessment of the model.

ROC -AUC is a common performance measure utilized to assess binary classification models. It evaluates a model's capacity to differentiate between categories at every potential decision threshold, yielding a single score that encapsulates overall ranking effectiveness. Scores vary from 0.0 to 1.0 and are usually classified as follows: 1.0 indicates a flawless model with complete reparability. A score of 0.90 to 0.99 signifies outstanding classification. A score between 0.80 and 0.90 indicates good performance. A score between 0.70 and 0.80 indicates that it is acceptable. A score between 0.50 and 0.60 indicates fair performance. A score of 0.50 signifies

random guessing (the model lacks discriminative ability), while a score below 0.50 suggests performance is inferior to random guessing (typically indicates mislabeled data).

PR-AUC assesses binary classification models by graphing precision versus recall at various probability thresholds. It is the benchmark metric for imbalanced datasets (such as fraud detection or disease diagnosis) since it disregards true negatives, concentrating exclusively on the infrequent positive class. PR-AUC is utilized in situations of significant data imbalance where the positive class is infrequent. In these situations, ROC-AUC may yield excessively optimistic outcomes since large quantities of true negatives falsely enhance performance metrics. In contrast to ROC-AUC, which has a random guessing baseline of 0.5, the baseline for PR-AUC is determined by the ratio of positive instances in the dataset. A score of 1.0 (Perfect Score) indicates that the model reaches 100% precision alongside 100% recall. Above Baseline indicates that the model has effectively learned to recognize positive instances more accurately than random guessing. At baseline (e.g., 0.02 in a 2% positive dataset), the model demonstrates no predictive capability; it is basically making random guesses or relying on majority voting. Typically, a score ranging from 0.80 to 1.0 indicates excellent to exceptional performance. A score between 0.50 and 0.80 is satisfactory, yet there's potential for enhancement. A score below 0.50 (or close to the baseline) indicates poor or restricted utility.

Brier score is a measure to assess the precision of probabilistic forecasts. It computes the average squared discrepancy between the expected probabilities and the real results. Scores vary from 0 to 1, with lower scores signifying improved model calibration and precision.

Sensitivity, also referred to as the true positive rate or recall, assesses the model's capacity to accurately recognize true positives. More specifically, sensitivity is the ratio of true positives to total positives. 1.0 (100%) represents an ideal score, indicating that the model correctly recognized all actual positive cases without any false negatives. Close to 1.0 (85% – 99%) indicates outstanding performance. Although a few positive cases might be overlooked, the model is very effective in recognizing most of the positive target class. Moderate (60% – 84%) indicates that the model is lacking a considerable number of positive cases. Below 0.5 (less than 50%) indicates Weak performance. The model fails to identify more real positive cases than it does, resulting in worse performance than a coin flip.

Specificity, or True Negative Rate, assesses the model's effectiveness in accurately recognizing genuine negative instances. A top score indicates that the model effectively reduces False Positives.

Precision is a metric that assesses the trustworthiness of a model's positive predictions. It addresses the inquiry: "When the model forecasts the positive class, how frequently is it truly accurate?" Mathematically, it represents the proportion of True Positives to the total predicted positives (True Positives + False Positives). This metric tells us what percentage of all the model's predictions about a sample being positive were correct. Precision is important when we want to avoid false positive predictions, for example in problems sensitive to false positives.

F1_Score assesses a classification model by computing the harmonic average of precision and recall. It is very effective for datasets with uneven classes, as it imposes penalties for significant disparities between the two metrics. 1.0 (ideal Score) signifies that the model has attained flawless precision and flawless recall. A high score (typically ≥ 0.7) reflects a solid equilibrium between precision and recall. The model accurately detects positive instances while reducing the occurrence of false positives and false negatives. A Low Score (typically < 0.5) suggests that one metric is much greater than the other. A score of 0.0 (worst Score) means the model did not detect any true positives, resulting in zero precision/recall.

Statistical analysis

Patient characteristics were presented using frequencies (percentage). The chi-square test and Fisher's exact test were used for categorical variables. Pearson Correlation, a statistical approach that evaluates the correlation between two data objects was utilized to assess the relationship between characteristics and PPH. Accuracy, sensitivity, specificity, precision, F1 Score, ROC AUC, PR-AUC, and Brier score were utilized to assess the performance of ML models in predicting PPH. All statistical analyses were done using SPSS (version 25.0, IBM Corp. Armonk, NY, United States) and Python software (Version 3.7.0). All statistical tests were two-tailed; $p < 0.05$ was considered statistically significant.

Results

Characteristics of the study population

Throughout the study phase, 1,044 expectant mothers were assessed for eligibility. Six hundred fifty-six individuals consented to participate in the study, and after excluding 52, data from 604 individuals were analyzed. Among the 604 eligible participants, 55 (9.10%) experienced PPH. Concerning the extent of bleeding, out of the 55 participants with PPH, 44 (80%) were categorized in the 1,000–1,500 cc range, 10 (18.18%) in the 1,500–2,000 cc range, and 1 (1.81%) in the 2,000–3,000 cc range. No instances were noted in the group exceeding 3,000 cc. Out of 55 postpartum hemorrhage cases, 46 resulted from uterine atony, while the others were caused by a wide episiotomy (one case), cervical laceration (five cases), retained placenta (one case), placenta previa (one case), and uterine inversion (one case).

The majority of mothers fell within the 18–35 age range, comprising 77.48% of the total samples. The obstetric characteristics of participants revealed that 31.95% were first-time mothers. 24.66% reported a history of abortion. Regarding the delivery method, findings indicated that 23.84% of the samples underwent cesarean sections, while 76.16% experienced vaginal deliveries.

Regarding clinical variables, 23.50% of participants experienced gestational diabetes, while preeclampsia was noted in 11.90% of the cases. The rates of chronic hypertension and gestational hypertension were low, recorded at 2.81% and 1.32%, respectively. Furthermore, smoking status and substance use were uncommon, reported positively in merely 0.49% and 0.82% of the samples, respectively. This suggests that these variables probably possess minimal predictive ability in the model because of their extremely low occurrence.

The differences of PPH and non-PPH cases regarding clinical characteristics

Table 1 illustrates the relationship between different characteristics and PPH using Chi-square and Fisher exact tests. Significant variations were observed in serum lactate levels between PPH and non-PPH instances. Elevated lactate serum was linked to PPH. Preeclampsia and gestational age were also associated with PPH. PPH was less common in preterm deliveries and those with previous cesarean sections ($p < 0.05$). PPH was more prevalent in women over 35 and multiparous women, though these latter differences were not statistically significant ($p = 0.60$, $p = 0.61$).

Table 1
The differences of PPH and non-PPH cases regarding clinical and laboratory factors

Features	PPH (n = 55)	Non-PPH (n = 549)	p-value
Serum lactate level Lactate > 4 mmol/L	50 (90.90%)	326 (59.38%)	0.000
Preeclampsia	10 (18.18%)	62 (11.29%)	0.031
Gestational age Term Preterm	47 (85.46%) 8 (14.54%)	432 (78.68%) 117 (21.32%)	0.045
History of previous cesarean	2 (3.63%)	72 (13.11%)	0.046
Maternal age 18–35 Less than 18 Above 35	43 (78.18%) 7 (12.72%) 5 (9.09%)	425 (77.41%) 106 (19.30%) 18 (3.27%)	0.060
Parity Primi-parity Multi-parity	26 (47.27%) 29 (52.73%)	347 (63.20%) 202 (36.80%)	0.061
Body Mass Index (Kg/m ²) 18-24.9 25-29.9 More than 30	20 (36.36%) 21 (38.18%) 14 (27.46%)	131 (23.86%) 300 (54.64%) 118 (21.49%)	0.495
Pre-delivery Hemoglobin Less than 11.0 g/dl	10 (18.18%)	89 (16.21%)	0.502
Fibrinogen level Less than 400 mg/dL	4 (7.27%)	68 (12.38)	0.507
History of Abortion	11 (20%)	138 (25.13%)	0.511
Gestational Hypertension	1 (1.81%)	7 (1.27%)	0.536
Gravidity Primigravida Multigravida	21 (38.19%) 34 (61.81%)	172 (31.33%) 377 (68.67%)	0.542

Features	PPH (n = 55)	Non-PPH (n = 549)	p-value
Method of Birth	11 (20%)	133 (24.23%)	0.618
Cesarean	44 (80%)	416 (75.77%)	
Vaginal birth			
Chronic Hypertension	2 (3.63%)	15 (27.27%)	0.661
Diabetes (Overt/Gestational)	12 (21.81%)	130 (23.67%)	0.868
Smoking	0	3 (0.54%)	
Substances use	0	5 (0.91)	0.999

Correlation between clinical characteristics and PPH

Pearson Correlation, a statistical approach that evaluates the correlation between two data objects, was utilized to assess the relationship between characteristics and PPH. As shown in Fig. 1, the strongest positive correlation was found with serum lactate levels. This observation indicates that as lactate levels rise, the likelihood of encountering PPH also somewhat increases. Following that, gestational age and preeclampsia additionally exhibited a positive correlation with PPH. Conversely, several variables displayed a negative correlation with PPH. The strongest negative correlation was associated with a past history of cesarean delivery. Parity and maternal age exhibited a slight negative correlation with PPH. (Fig. 1)

The performance of ML models in predicting PPH

Figure 2 illustrates the performance of the leading five models as determined by 10-fold cross-validation. In this graph, the diagonal line symbolizes random performance, and the models' curves being above this line suggests that the models have developed some capacity to differentiate between PPH and non-PPH patients. The Logistic Regression model delivered the highest performance, attaining an average ROC-AUC of 0.71. This value surpasses the random scenario and shows that the model could rank the likelihood of PPH occurrence slightly better than the alternative models. Next came AdaBoost (AUC = 0.66), Random Forest (AUC = 0.65), Linear SVM (AUC = 0.64), and Naive Bayes (AUC = 0.64).

In terms of curve shapes, Logistic Regression is positioned higher than the other models-and above the random chance line-for a considerable section of the plot. This corresponds with the numerical findings in the table, affirming that Logistic Regression exhibited the greatest overall discriminative ability. The shaded regions around the curves are quite broad, suggesting variability in the model's performance across the various folds. Consequently, although performance has improved, model stability remains suboptimal, and the outcomes should be viewed with caution.

When assessing the models using 10-fold cross-validation, the findings indicated that while the Logistic Regression model outperformed others with an average ROC-AUC of 0.71, and a Brier score of 0.07, analysis of additional metrics revealed it did not adequately predict PPH. A comparable trend was noticed in numerous models. Models like AdaBoost, Linear SVM, Random Forest, RBF SVM, and KNN (7) exhibited extremely high specificity, nearing 1.00, while their sensitivity remained at 0. This indicates that these models recognized nearly all samples as non-PPH and essentially failed to identify any PPH cases at a threshold of 0.5. Consequently, the high

precision of these models is attributed more to the prevalence of the non-PPH group in the dataset than to their true capability in identifying PPH.

In comparison, the Naive Bayes model acted in a different manner. It exhibited a remarkable sensitivity of 0.935 and detected the majority of PPH instances, but demonstrated a significantly low specificity of 0.130. This indicates that it wrongly classified many non-PPH cases as PPH. Its accuracy was quite low (0.203), and the Brier score was notably high (0.797). Consequently, even with the improved PR-AUC, Naive Bayes lacks reliability in overall prediction accuracy and probability outputs. The LightGBM and XGBoost models identified a limited number of positive cases, yet their sensitivity remained low, approximately 0.045. This suggests that these models had a marginally better performance than models with zero sensitivity, yet were still inadequate for identifying PPH cases. (Table 2)

Table 2
The performance of ML models in predicting PPH.

Model	Accuracy	ROC_AUC	PR_AUC	Brier	Sensitivity	Specificity	Precision	F1_Score
AdaBoost	0.90	0.65	0.18	0.13	0	1	0	0
CatBoost	0.89	0.58	0.15	0.09	0	0.98	0	0
Decision Tree	0.90	0.59	0.18	0.08	0	0.99	0	0
KNN (5)	0.90	0.51	0.17	0.10	0.02	0.98	0.05	0.02
KNN (7)	0.90	0.54	0.14	0.09	0	1	0	0
LightGBM	0.89	0.60	0.19	0.09	0.04	0.98	0.10	0.06
Linear SVM	0.90	0.64	0.27	0.08	0	1	0	0
Logistic Regression	0.90	0.71	0.27	0.07	0.02	0.99	0.10	0.04
Naive Bayes	0.20	0.64	0.36	0.79	0.93	0.12	0.09	0.17
Neural Net	0.88	0.57	0.15	0.09	0.02	0.97	0.03	0.02
RBF SVM	0.90	0.42	0.08	0.08	0	1	0	0
Random Forest	0.90	0.65	0.21	0.08	0	1	0	0
XGBoost	0.89	0.60	0.20	0.08	0.04	0.97	0.15	0.06

Discussion

Out of the 604 qualified participants, 55 (9.10%) encountered PPH. Global PPH rates vary significantly depending on the region, hospital setting, and whether blood loss is measured objectively or estimated subjectively. Globally, around 1 in 10 women experience PPH, with severe bleeding rates differing considerably across published research [25]. Nonetheless, our occurrence was close to the average global rate.

In the initial traditional statistical analysis of our study, comparing the PPH group to the non-PPH population revealed significant variations in serum lactate levels. An increased serum lactate level (hyperlactatemia) arises when there is a disparity between lactate generation and elimination in the body. Standard levels usually range from 0.5 to 1.0 mmol/L, while levels exceeding 2.0 mmol/L indicate distress. It serves as an essential indicator of tissue hypoxia, shock, and serious systemic disease [26]. It is essential to recognize that lactate levels can naturally rise (up to ~ 4.0 mmol/L) during a typical, physically challenging labor, but persistent increases after delivery require careful monitoring for PPH [27]. In the event of significant, active bleeding, the volume of circulating blood diminishes, leading to a reduction in blood pressure and a decrease in oxygen supply to essential organs. To make up for the deficit of oxygen, cells transition from aerobic energy generation to anaerobic metabolism, resulting in lactic acid as a byproduct. As a result, increasing serum lactate concentrations act as a quantifiable sign that a patient is progressing towards hemorrhagic shock [28]. In PPH, increased serum lactate signifies tissue hypoperfusion (insufficient oxygen supply to tissues) caused by substantial blood loss and hemodynamic instability. It serves as an essential, early predictive indicator to predict the necessity for extensive blood transfusions and admission to intensive care [29].

Clinical studies demonstrate that serum lactate levels do not predict the onset of PPH during labor, but they are highly correlated with the severity of PPH, the need for massive transfusions (MT), and intensive care unit (ICU) admissions once bleeding occurs [30]. The scientific agreement categorizes lactate's clinical usefulness into two separate stages: its constraints during active labor and its significant prognostic strength in managing acute hemorrhage [31]. Our research revealed a significant relationship between serum lactate levels and PPH. Given that the lactate serum was measured right after birth within the first 15 minutes, we can assert that the rising lactate levels could align with the timing of bleeding when the PPH had not yet been clinically identified. Maybe the outcomes would have varied if lactate levels had been assessed during labor and before delivery. Future studies might benefit from serially monitoring lactate during labor, right after delivery, and when diagnosing PPH to enhance understanding of its association with bleeding incidence and severity.

According to our findings, PPH was also linked to gestational age. In contrast to the previous studies, PPH occurred less frequently in preterm births. A study indicates that the likelihood of PPH rises by roughly 7% for each extra week of delivery occurring before 37 weeks [32]. Preterm births are thought to have increased PPH rates primarily due to the medical issues that cause early delivery such as placental abnormalities, chorioamnionitis, and preeclampsia [33]. Although the general agreement in obstetrics indicates that preterm deliveries have a higher risk of PPH, certain studies and clinical groups have shown that PPH rates were either lower or similar in preterm births compared to full-term births [34]. The reason behind these controversial findings may stem from the isolation of specific variables—such as omitting significant pregnancy complications or concentrating on particular types of pregnancies like singleton pregnancies—leading to unexpected results in the data.

Preeclampsia as expected was linked to PPH based on our findings. Preeclampsia greatly raises the risk of PPH, nearly doubling the chances in comparison to uncomplicated pregnancies [35]. Preeclampsia damages blood vessels and interferes with the body's ability to manage blood flow after childbirth. In severe instances of preeclampsia—such as HELLP syndrome (Hemolysis, Elevated Liver enzymes, Low Platelets)—the body's blood-clotting mechanisms are disrupted, hindering the management of bleeding, which may result in PPH [36].

Based on literature women who have had a prior cesarean delivery face an elevated risk of PPH than that of those who gave birth vaginally. This risk is mainly influenced by conditions related to uterine scars, pelvic adhesions, and abnormal placentation (like placenta previa or accreta), complicating future cesarean sections [37]. In our study

PPH was less common in those with a history of previous cesarean. Although a history of prior cesarean is a recognized physiological risk factor for PPH, certain clinical studies indicate decreased PPH rates in these individuals [38]. This surprising result is typically attributed to proactive medical management, variations in study design, or choices in delivery tracking, rather than an inherent biological benefit. Obstetric teams automatically classify patients with a history of cesarean as high-risk. Due to their anticipation of bleeding, doctors take proactive aggressive preventative actions that they may not employ for low-risk, first-time vaginal deliveries. A planned repeat cesarean before labor mitigates the dangers of extended labor, and emergency procedures, all of which significantly increase the likelihood of PPH. These could be the factors contributing to the reduced rate of PPH in prior cesarean sections within our study group.

In the advanced phase of our analysis, we employed ML models to assess the significance of risk factors in predicting PPH. Our results indicated that the Logistic Regression model exceeded the performance of the others, achieving an average ROC-AUC of 0.71 and a Brier score of 0.07; however, additional metrics (sensitivity: 0.02, precision: 0.10, F1Score: 0.04) suggested it was inadequate in effectively predicting PPH. Systematic reviews indicate that the accuracy of ML models in predicting PPH is highly variable, with ROC-AUC scores spanning from a low 0.51 to an almost flawless 0.97 [14]. This significant degree of variation happens because studies employ different methods that are not standardized. The primary causes for these varied outcomes lie in four key areas: inconsistent definitions of PPH, variations in data timing and availability (selection features), significant data imbalance and sample sizes, and technical as well as algorithmic weaknesses. Nonetheless, a few recent studies have shown the strong capability of various algorithms in predicting PPH, which is very encouraging [14, 39].

Recognizing a risk factor is beneficial only if it prompts particular, proactive clinical measures before and right after delivery. This predictive model is especially useful for assessing risk before the occurrence of significant bleeding. In the subsequent phase, advanced health networks can utilize automated ML algorithms incorporated into hospital electronic health records (EHR) systems. These tools continually collect a patient's lab results and labor notes in the background, automatically alerting the obstetric team if a patient's specific PPH risk index exceeds a crucial threshold.

Even with their greater precision, AI predictive models encounter specific challenges before they can be widely adopted in labor wards. The majority of AI models are developed using particular, information-rich hospital networks. Their accuracy frequently decreases when used in various patient groups or in settings with limited resources [40, 41]. Executing real-time AI models necessitates sophisticated EHR systems that can provide immediate lab results and clinical data directly to the algorithm. Since clinicians struggle to understand why an AI algorithm unexpectedly identifies a patient as high-risk, incorporating these "black box" tools into quick-response workflows continues to be difficult [42].

The most important challenge is the ability of laboratories to provide patient test results in the shortest possible time. If this does not happen, the patient may bleed before receiving the laboratory results, and then the predictive power of the test results will have no clinical impact on preventive measures to help the patient. Standard laboratory turnaround times for fibrinogen, lactate, and hemoglobin differ greatly based on whether they are requested as "Emergency" or "Routine," and whether they are processed through the central laboratory or through bedside Point-of-Care Testing [43]. In critical clinical situations—like handling severe PPH or shock—these tests are consistently regarded as emergency markers. Centralized lab reporting durations inherently comprise pre-analytical processes (blood collection, labeling, pneumatic tube transport, and centrifugation). Testing in the central lab typically requires 45 to 60 minutes for an urgent order. In comparison, point-of-care devices reduce this

processing time to less than 10 minutes at the patient's side [44]. Taking these factors into account, it appears that the serum lactate level measured immediately after childbirth could be beneficial in anticipating the requirement for significant interventions like massive blood product transfusion, instead of forecasting PPH itself. All these constraints should be considered for future analysis.

Conclusion

The Pearson correlation showed a strong positive relationship among serum lactate levels, gestational age, history of cesarean, and preeclampsia related to PPH; however, the predictive performance of the ML models for PPH was poor. This result underscores a fundamental statistical issue: correlation does not ensure predictability. A Pearson correlation reveals linear patterns throughout a full dataset, whereas ML models need clear, separate boundaries to yield precise individual predictions. Additional research involving a larger sample and more predictive variables is required for improved conclusions.

Abbreviations

PPH

Postpartum hemorrhage

WHO

World health organization

MMR

Maternal mortality ratio

AI

Artificial intelligence

ML

Machine learning

BMI

Body mass index

EHR

Electronic health record

ROC-AUC

Receiver operating characteristic - area under the curve

PR-AUC

Precision-Recall area under the curve

SVM

Support vector machine

RBF SVM

Radial Basis Function Support Vector Machine

KNN

k-nearest neighbors

Declarations

Ethics approval and consent to participate

This study complied with the Declaration of Helsinki and was performed according to ethics committee approval. The Ethics and Research Committee of the Iran University of Medical Sciences approved the study (IR.IUMS.REC 1403.1140). The records of all patients who provided written informed consent for using their data for research purposes were analyzed. For individuals below eighteen years old, consent was obtained from their guardians. Statistical analysis was performed with patient anonymity following ethics committee regulations.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Author contributions

F.F. and N.H. wrote the proposal. F.F., A.R., M.D., and E.K. contributed significantly to data collection. The findings were analyzed and interpreted by F.F. and N.H. The manuscript's scientific content was assessed critically by M.K., T.E.B., M.M. and N.E. The final manuscript for submission was read and approved by all authors.

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Figures

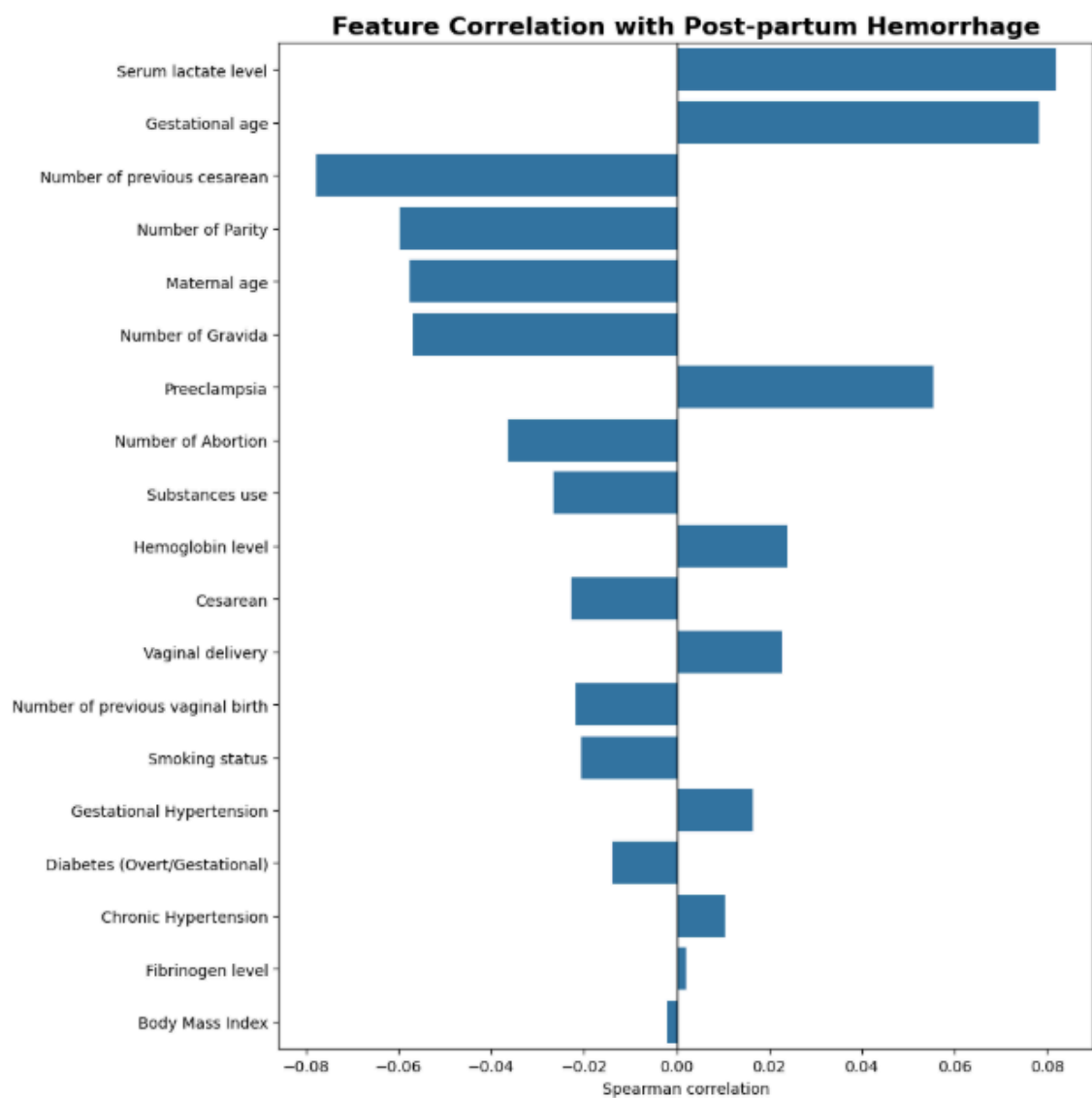


Figure 1

Spearman correlation between clinical factors and PPH.

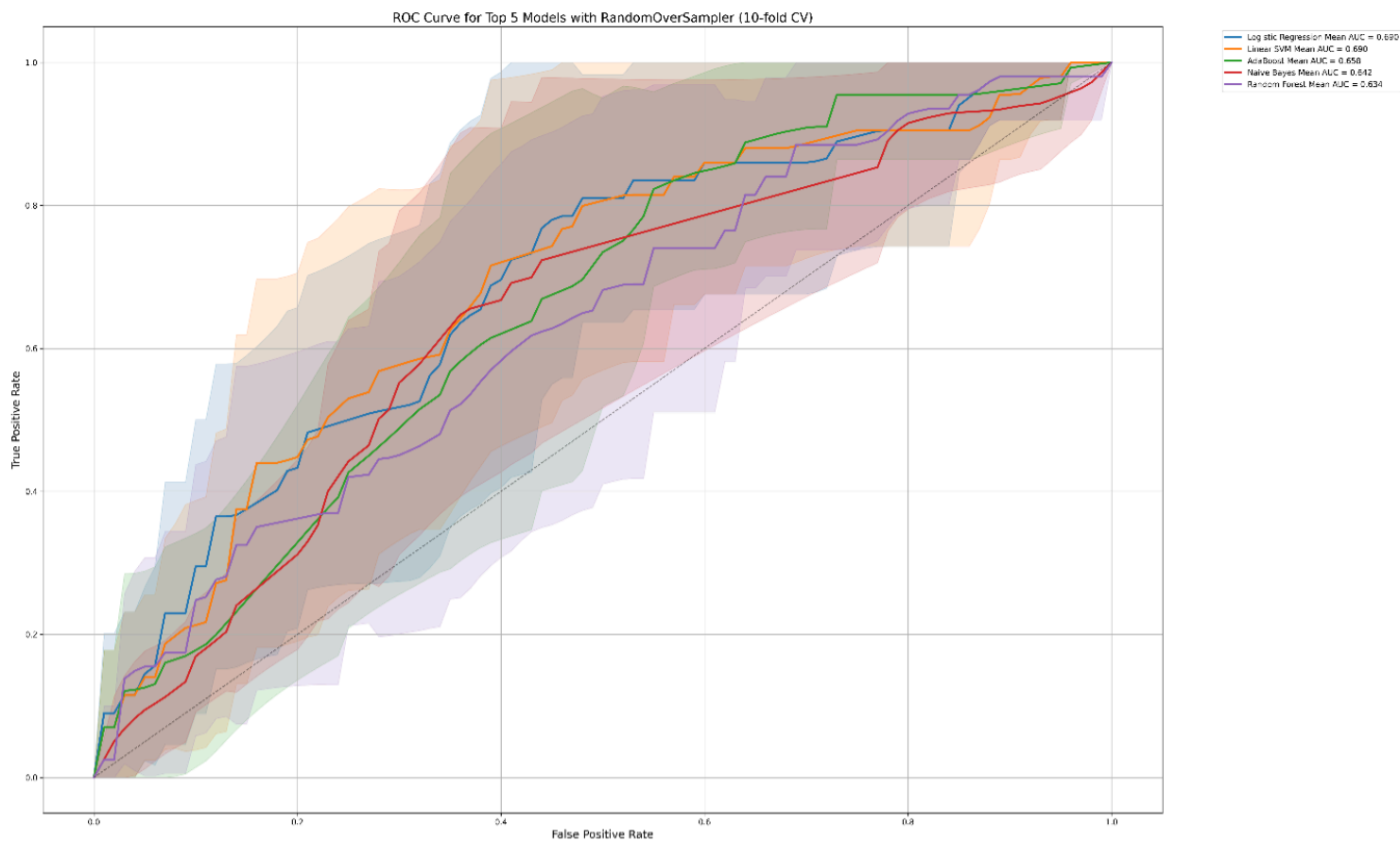


Figure 2

ROC-AUC of ML models in predicting PPH.

Supplementary Files

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