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JTH

https://jthkkss.com/
e-ISSN 2805-4431
DOI: https://doi.org/10.53797/jthkkss.v7i1.6.2022

Enhancing Maternal Health: Logistic Regression for Predicting Postpartum Hemorrhage

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Received 30 November 2025; Accepted 01 January 2026; Available online 15 May 2026

Abstract: Postpartum hemorrhage (PPH) is a leading cause of maternal mortality, especially in developing countries like Indonesia, where the Maternal Mortality Rate (MMR) remains high. Machine learning (ML) can enhance early PPH prediction, improving risk identification and clinical decision-making. Logistic Regression (LR) has shown strong performance in PPH prediction, with accuracy ranging from 69–92%. This study evaluates ML algorithms to improve PPH risk prediction and support timely clinical interventions. A retrospective cohort study analyzed 1,029 birth cases (326 PPH, 703 non-PPH) with 21 features covering maternal profiles, obstetric history, and health status. A logistic regression model was developed, utilizing SMOTE for class balancing and enhanced with Particle Swarm Optimization (PSO) and Evolutionary Feature Selection (EFS). EFS without SMOTE achieved the highest accuracy (86.78%) but had an imbalance with high sensitivity (93.74%) and low specificity (71.79%). PSO with SMOTE, while slightly less accurate (84.43%), had the highest AUC (0.905) and better balance between sensitivity (86.16%) and specificity (82.66%), effectively addressing class imbalance. Key PPH predictors include birth attendant, prolonged labor, and anemia level.

Keywords: Evolutionary Feature Selection, Logistic Regression, Postpartum Hemorrhage, Particle Swarm Optimization, SMOTE

1. Introduction

PPH remains a predominant contributor to maternal morbidity and mortality on a global scale. Accurate early identification and timely intervention are imperative to mitigate the risks associated with PPH (World Health Organization, 2023). The incidence of PPH varies significantly between countries, influenced by differences in definitions, methods of measuring postpartum blood loss, and social and demographic factors (Amanuel et al., 2021).

PPH refers to abnormal bleeding following childbirth, typically characterized by a blood loss exceeding 500 ml after a vaginal delivery or 1000 ml after a cesarean section (Higgins et al., 2019). Various factors, including uterine atony, trauma, retained placenta, and clotting disorders, can contribute to PPH. Identifying women at high risk for PPH before or during labor is crucial in minimizing the risk of severe complications, which may result in shock, organ failure, or even death (Gill et al., 2022). Currently, PPH cases are still mostly dominated by developing countries with middle to lower economic levels. The maternal mortality rate (MMR) in 2017 shows that globally there were 211 maternal deaths per 100,000 live births, with 41 of them occurring in countries with a lower middle economic level (Tiruneh et al., 2022). However, PPH can also occur in developed countries, although with lower frequency (Bláha & Bartošová, 2022). The

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MMR in Indonesia is still far from the 2030 SDGs target of 70 per 100,000 live births (SDGs, 2019). Based on the 2017 SDKI, the Maternal Mortality Rate (MMR) in Indonesia is around 305 per 100,000 live births, which has not yet reached the 2024 RPJMN target of 183 per 100,000 live births. One of the biggest causes of maternal death after preeclampsia is PPH (Kemenkes RI., 2021).

Maternal mortality is a global health problem that can be prevented by exploring Machine Learning (ML) approaches to reduce mortality. By utilizing historical maternal health data, machine learning can develop predictive models, early detection systems, and improve monitoring and access to care (Rahmatullah, 2019; Zhang et al., 2023). This allows for more targeted interventions and improved quality of health services (Neha Margret et al., 2024; Rahmatullah & Besar, 2009). As technology integration in the healthcare sector increases, ML algorithms show significant potential to improve diagnostic accuracy and clinical prediction (Namburete et al., 2013; Rahmatullah & Noble, 2014; Sunarti et al., 2021).

ML techniques have the power to identify nonlinear relationships and interactions between variables, with promising results in PPH prediction (Huang et al., 2021; Sinambela et al., 2024; Westcott et al., 2022). However, some studies show that the predictive performance of ML is limited compared with classical methods such as simple statistics, mainly because ML requires large amounts of data, making it less suitable for small datasets or with few significant events (Abuelezz et al., 2022; Park et al., 2021). Some studies only show the performance of ML without comparison with simpler methods. Logistic Regression is one of the most commonly utilized machine learning techniques for prediction tasks. This algorithm is widely employed in health research due to its ability to assist healthcare professionals in making clinical decisions (Liu et al., 2022). The outcomes of this model can offer potential disease classification, predict responses to treatment, and assess the risk of recurrence, thus enhancing the accuracy and data-driven nature of the decision-making process (Shipe et al., 2019). According to (Nusinovici et al., 2020), logistic regression succeeded in showing the best performance with a ROC value of 0.905, superior to neural networks, SVM, and gradient boosting in predicting chronic diseases in patients. This is due to the high ROC value, which shows the effectiveness of the logistic regression model in differentiating patients who suffer from chronic diseases.

Based on previous research regarding PPH prediction using a machine learning approach shows that the logistic regression (LR) algorithm provides good performance. According to (Akazawa et al., 2021), logistic regression was found to be the model with the best performance for predicting PPH with an accuracy value of 69%. Furthermore, research by (Ries et al., 2020) reported that logistic regression achieved the highest performance with an accuracy of 92%. The objective of this study was to evaluate the performance of the ML algorithm, particularly LR, in predicting PPH using maternal clinical data. The study also aims to develop a model that uses the algorithm to assign a probability score to each patient, helping clinicians identify those at higher risk of developing PPH.

2. Methodology

This study used a retrospective cohort design and employed various data collection methods. The process model included the following stages:

2.1 Dataset

The study sample comprised 326 cases (women with PPH) and a control group of 703 women without PPH. Cases were selected using total sampling, while the control group was determined through systematic random sampling. Data were obtained from the medical records of Ansari Saleh General Hospital in Banjarmasin, covering the period from 2018 to 2022, as presented in Table 1.

Table 1: Features from the medical record

No	Categorical Data	Features
1	Profile	Maternal Age, Gravidity, Gestational Age
2	Obstetric	Gestational Hypertension, Birth Attendant, Baby's Birth Weight, Breech Birth, Delivery Method, Antenatal Care Attendance, Severe Preeclampsia, Premature Rupture of Membrane, Prolonged Labor, Placenta Previa, History of CD, Cephalopelvic Disproportion, Oligohydramnios, History of Abortion, referral system
3	Health	Anemia Level, BMI, Hepatitis B Blood test

2.2 Predictive Model

To develop a PPH prediction model using a machine learning approach with a logistic regression algorithm, several systematic stages were conducted (Venkatesh et al., 2020; M. Wang et al., 2024). The analysis study was carried out using a dataset that had undergone a preprocessing process. The dataset was analyzed with the Rapid Miner program to identify performance values in predicting PPH (Kauser Ahmed, 2017). First, data preprocessing was performed on 1,029 birth cases, comprising 326 PPH cases and 703 non-PPH cases. This stage involved handling missing values, normalizing data, and ensuring consistent data formatting. Second, to address the class imbalance between PPH and non-PPH cases, the Synthetic Minority Over-Sampling Technique (SMOTE) was applied, creating a more balanced class distribution (S. Wang et al., 2021). Third, the prediction model was constructed using a logistic regression algorithm with cross-validation at k-fold levels of 3, 5, and 10 (Akazawa et al., 2021; Misra & Yadav, 2020). The analysis was divided into two phases: initially, the model was developed using all 21 features without feature selection; subsequently, the model was enhanced by integrating SMOTE with feature optimization techniques, including PSO and EFS, to improve prediction accuracy.

The model's performance was evaluated using key metrics: accuracy, Area Under the Curve (AUC), sensitivity, specificity, and Receiver Operating Characteristic (ROC). This methodological framework ensures the resulting model achieves optimal performance in predicting PPH incidence, despite challenges posed by class imbalance and a high number of predictor variables. In addition, a correlation-based weight analysis was conducted to identify the most influential features associated with PPH incidence, highlighting the importance of key predictors in the model. The overall workflow of the proposed PPH prediction model, including data preprocessing, class imbalance handling using SMOTE, feature optimization using EFS and PSO, and model evaluation, is illustrated in Figure 1.

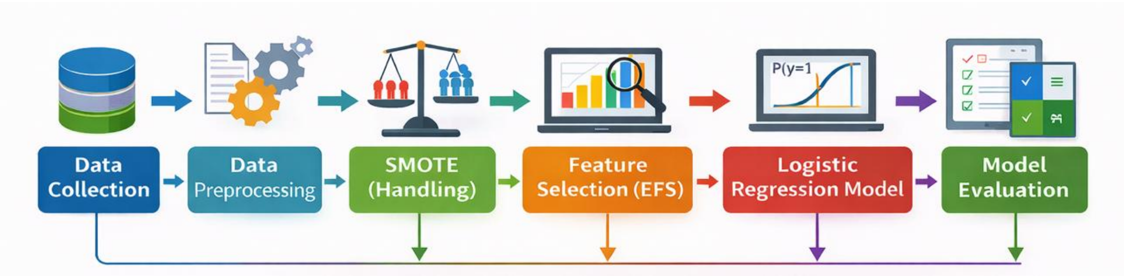

Fig. 1: Proposed Framework for Predicting Postpartum Hemorrhage

3. Findings and Discussion

The analysis in this research led to the creation of a PPH prediction model, carefully developed through a systematic and well-defined sequence of stages designed for robust model creation.

3.1 Dataset

Table 2 illustrates the frequency and percentage distribution of respondent profiles categorized by maternal characteristics. The data indicate that most participants belonged to the category that depicts the frequency distribution and percentage of participant profiles categorized based on profile, obstetric, and health characteristics. The table presents a wide array of data, showing various factors that can influence pregnancy outcomes, especially those related to conditions like postpartum hemorrhage (PPH). The distribution highlights key trends such as the prevalence of antenatal care attendants, birth attendants, and the occurrence of conditions like severe anemia, gestational hypertension, and preeclampsia. It provides a comprehensive overview of maternal and obstetric characteristics that may play a role in the risk of PPH and other childbirth complications.

Table 2: Clinical profile of women with PPH and without PPH

Categorical Data	Features	Specific feature	Frequency	Percentage (%)
Profile	Maternal Age	< 20	148	14.38
		20-34	669	65.01
		≥ 35	212	20.6
	Gravidity	Multiparous	573	55.69
		Primiparous	393	38.19
		Grand Multiparous	63	6.12
	Gestational Age	< 37 weeks	114	11.08
		> 42 weeks	34	3.3
		37-42 weeks	851	82.7
Obstetric	Gestational Hypertension	Yes	141	13.7
		No	888	86.3
	Birth Attendant	Gynaecology Obstetrician	743	72.21
		Midwife	190	18.46
		Untrained Birth Attendant	5	0.49

continued

Categorical Data	Features	Specific feature	Frequency	Percentage (%)
	Baby's Birth Weight	< 2.500 grams	104	10.11
		> 4.000 grams	21	2.04
		2.500-4.000 grams	904	87.85
	Breech Birth	Yes	55	5.34
		No	974	94.66
	Delivery Method	Normal Delivery	752	73.08
		Caesarean Delivery	250	24.3
		Vacuum Extraction	27	2.62
	Antenatal Care Attendance	< 6	248	24.1
		≥ 6	781	75.9
	Severe Preeclampsia	Yes	190	18.46
		No	839	81.54
	Premature Rupture of Membrane (PROM)	Yes	179	17.4
		No	850	82.6
	Prolonged Labour	Yes	105	10.2
		No	924	89.8
	Placenta Previa	Yes	37	3.6
		No	992	96.4
	History of Caesarean Delivery	Ever	118	11.47
		Never	911	88.53
	Cephalopelvic Disproportion	Yes	38	3.69
		No	991	96.31
	Oligohydramnios	Yes	32	3.11
		No	997	96.89
	History of Abortion	Ever	113	10.98
		Never	916	89.02
	Referral System	Referral	459	44.61
		Without Referral	570	55.39
Health	Anaemia Level	Mild Anaemia	192	18.66
		Moderate Anaemia	192	18.66
		Severe Anaemia	588	57.14
		Not Anaemia	57	5.54
	Body Mass Index (BMI)	Underweight	90	8.75
		Normal Weight	753	73.18
		Overweight	134	13.02
		Obesity Class 1	44	4.28
		Obesity Class 2	9	0.87
	Hepatitis B Blood Tests	Positive	31	3.01
		Negative	998	96.99

3.2 Predictive Model

Table 3 below presents the results of the PPH prediction analysis using a logistic regression algorithm approach in order to evaluate the performance value of the model. The table shows that shuffled sampling provides the highest accuracy value compared to other parameters. The shuffled sampling parameters show that the best application of the logistic regression model produces an accuracy of 85.34%, precision of 86.78%, sensitivity of 92.52%, specificity of 98.98%, and an AUC of 0.898. Shuffled sampling provides better results because it divides the data randomly, reducing bias in selecting training and testing data. By randomizing the order of the data, the model can learn from a wider range of patterns, reducing overfitting and increasing its generalization capabilities. This contributes to increased accuracy, precision, sensitivity, specificity, and AUC, resulting in more optimal performance in the logistic regression model.

Table 3: The performance of Postpartum Hemorrhage using the Logistic Regression Algorithm

Sampling Technique	Cross-validation	Accuracy	AUC	Sensitivity	Specificity
Shuffled Sampling	3	84.35%	0.890	91.63%	68.74%
	5	85.32%	0.898	92.52%	70.14%
	10	85.32%	0.899	92.24%	70.40%
Stratified Sampling	3	85.03%	0.890	91.46%	71.15%
	5	85.23%	0.890	92.18%	70.28%
	10	84.93%	0.894	91.46%	70.89%

The table reveals an imbalance between sensitivity and specificity, most likely caused by data imbalance. Although the AUC value of 0.898 indicates good performance, there is still room for improvement. Logistic regression models often struggle to optimally address more complex classification problems, particularly when non-linear relationships or interactions exist between features. This imbalance in sensitivity and specificity can be mitigated by applying the SMOTE. SMOTE effectively addresses data imbalance by generating synthetic samples for minority classes, resulting in a more balanced data distribution (Feng et al., 2021; Tyagi et al., 2023). With a balanced dataset, the logistic regression model can learn patterns more effectively, leading to improvements in sensitivity, specificity, and overall model performance (Dube & Verster, 2023).

To further enhance model performance, it is essential to optimize the logistic regression algorithm. The optimization approach involves the application of PSO and EF. PSO utilizes population-based optimization principles to search for optimal parameters, while EFS identifies the best combination of features to improve model efficiency and accuracy (Bouakline et al., 2024). This combined approach not only enhances prediction accuracy and generalization capabilities but has also proven effective in identifying key risk factors contributing to case exposure. By doing so, it supports more accurate, data-driven decision-making. The combination of these two methods is often used in machine learning to handle high-dimensional problems, reduce overfitting, and increase the accuracy of prediction models. The results of this experiment, which illustrate the effect of optimization on model performance, are shown in Table 4.

Table 4: Comparison of PSO and EFS Methods with SMOTE in Logistic Regression Algorithm for Predicting Postpartum Hemorrhage

Optimization	Sampling Techniques	Accuracy	AUC	Sensitivity	Specificity
PSO	Without SMOTE	86.01 %	0.903	92.55 %	71.94 %
	With SMOTE	84.43 %	0.905	86.16 %	82.66 %
EFS	Without SMOTE	86.78 %	0.904	93.74 %	71.79 %
	With SMOTE	84.28 %	0.902	84.98 %	83.61 %

As shown in Table 4, it can be seen that EFS without SMOTE shows the highest accuracy value (86.78%), but there is a clear imbalance between sensitivity and specificity. This shows that although the model was able to detect positive cases well (sensitivity 93.74%), it had difficulty detecting negative cases (specificity 71.79%). Meanwhile, PSO with SMOTE, although it showed slightly lower accuracy (84.43%), had the highest AUC (0.905) and offered a better balance between sensitivity and specificity (86.16% and 82.66%). This indicates that the application of SMOTE in PSO optimization successfully overcomes data imbalance, resulting in a fairer model in predicting both classes.

In contrast, the PSO model with SMOTE, although yielding slightly lower accuracy (84.43%), achieved the highest AUC (0.905) and provided a more balanced performance between sensitivity (86.16%) and specificity (82.66%). This finding suggests that the integration of SMOTE with PSO effectively addresses class imbalance, resulting in a more robust and balanced model for predicting both PPH and non-PPH cases.

Overall, the combination of SMOTE with optimization (either with PSO or EFS) proves to be effective in dealing with data imbalance problems. This method not only improves the accuracy but also the fairness of the model in detecting both positive and negative cases. The choice between PSO and EFS depends on the analysis goals: PSO is more suitable for finding stable optimal parameters, while EFS focuses more on selecting the best features to improve model efficiency and accuracy (Jibril et al., 2023). Furthermore, the ROC curve analysis demonstrates that all models achieved good classification performance, with AUC values ranging from 0.902 to 0.905. The PSO with the SMOTE model achieved the highest AUC (0.905), indicating superior discriminative ability among the evaluated models, as illustrated in Figure 2.

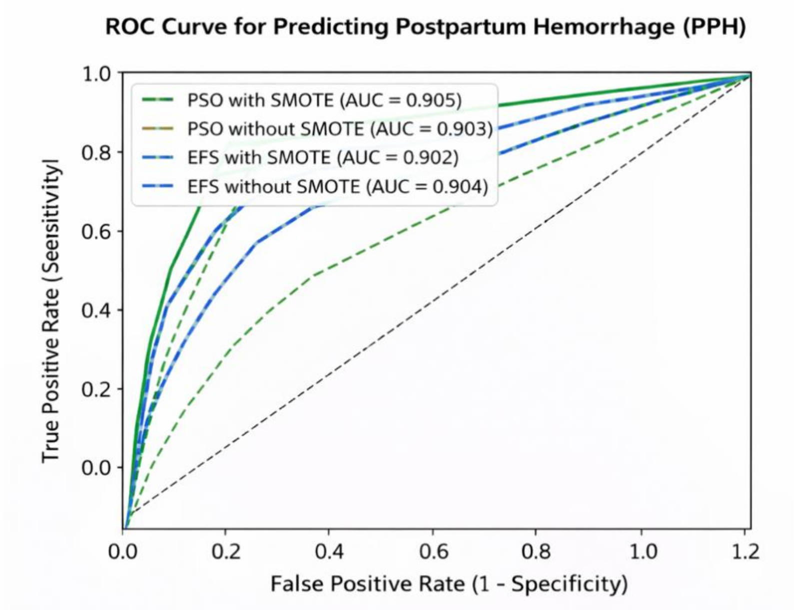

Fig. 2: ROC curve of LR models with PSO and EFS optimization, with and without SMOTE for predicting PPH

The performance of the proposed model was compared with that of the study by Goad et al. (2021), which reported an AUC of 0.82, sensitivity of 92.0%, and specificity of 72.5%. In contrast, the proposed model achieved a higher AUC of 0.905 using PSO with SMOTE, indicating superior discriminative ability. Although the sensitivity of the proposed model (86.16%) is slightly lower, its specificity (82.66%) is substantially higher, resulting in a more balanced performance in identifying both PPH and non-PPH cases. This improvement can be attributed to the integration of SMOTE for handling class imbalance and optimization techniques (PSO and EFS) for feature selection and parameter tuning. Overall, the proposed approach provides a more robust and balanced model for PPH.

Despite these promising findings, this study has several limitations. First, the dataset was derived from a single healthcare institution, which may limit the generalizability of the results. Second, although LR provides high interpretability, it may not adequately capture complex nonlinear relationships among predictors. Third, while SMOTE was applied to address class imbalance, the generated synthetic samples may not fully represent real-world clinical conditions. Therefore, future studies should incorporate external validation using multicenter datasets and explore more advanced machine learning approaches.

Finally, identifying key features is essential in machine learning to predict PPH cases effectively. Feature selection enhances model accuracy by focusing on relevant attributes, reducing complexity, and improving efficiency. Figure 3 highlights the selected features based on their impact on predictions and model performance. According to Figure 3, factors such as birth attendants, breech birth, and prolonged labor are the most influential in the incidence of PPH

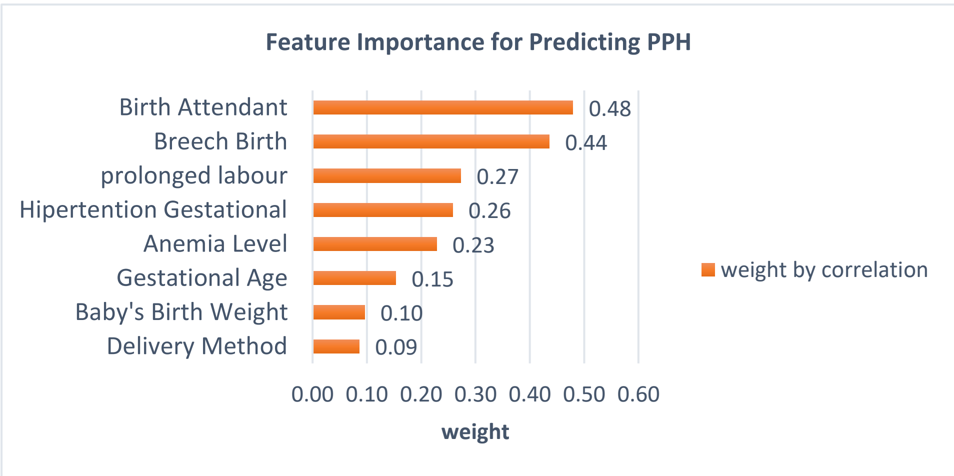

Fig. 3: Analysis of the important features influencing PPH using Logistic Regression

4. Conclusion

Machine learning techniques, including logistic regression, are poised to revolutionize the way postpartum hemorrhage is predicted and managed. As more data becomes available and algorithms continue to improve, predictive models will become increasingly accurate and integrated into clinical workflows. By empowering healthcare providers with reliable tools for early prediction, machine learning can play a pivotal role in reducing maternal mortality and improving patient outcomes. In the future, machine learning models may evolve to incorporate more complex algorithms, such as ensemble methods or deep learning, to further enhance prediction accuracy. Collaborative efforts between healthcare professionals, data scientists, and machine learning engineers will be crucial in realizing the full potential of these technologies. The application of logistic regression for PPH prediction is an exciting example of how machine learning can improve maternal health outcomes. By leveraging data and advanced algorithms, healthcare providers can make more informed decisions, ultimately save lives and improve the care of mothers worldwide. As the field of medical machine learning continues to advance, it is clear that smart predictions are the future of healthcare.

Acknowledgement

The authors would like to express their gratitude for the financial support provided by Sari Mulia University, Banjarmasin, Indonesia. Special thanks also go to the participants for their involvement, which greatly contributed to the successful completion of the research.

Conflict of Interest

The authors declare no conflict of interest

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