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Machine learning approaches for predicting postpartum hemorrhage: a comprehensive systematic literature review

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ABSTRACT

Postpartum hemorrhage (PPH) represents a significant threat to maternal health, particularly in developing countries, where it remains a leading cause of maternal mortality. Unfortunately, only 60% of pregnant women at high risk for PPH are identified, leaving 40% undetected until they experience PPH. To address this critical issue and ensure timely intervention, leveraging rapidly advancing technology with machine learning (ML) methodologies for maternal health prediction is imperative. This review synthesizes findings from 43 selected research articles, highlighting the predominant ML techniques employed in PPH prediction. Among these, logistic regression (LR), extreme gradient boosting (XGB), random forest (RF), and decision tree (DT) emerge as the most frequently utilized methods. By harnessing the power of ML, we aim to foster technological advancements in the healthcare sector, with a particular focus on maternal health and ultimately contribute to the reduction of maternal mortality rates worldwide.

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1. INTRODUCTION

Postpartum hemorrhage (PPH) is excessive bleeding after childbirth, defined as over 500 ml after vaginal delivery or 1000 ml after a cesarean section [1]–[4]. A global health concern, PPH is the leading cause of maternal mortality, responsible for about 6% of all maternal deaths, with developing nations, especially low-income countries, bearing the highest burden [5]–[8]. In Indonesia, maternal complications, including PPH, contribute significantly to maternal fatalities, with 1,280 reported cases [9], [10].

Effectively managing PPH requires prompt recognition of risk factors and responding to excessive bleeding. Diagnosing PPH is challenging due to underestimated blood loss and variable presentation of risk factors. Current guidelines emphasize the importance of vigilance and proactive measures to address PPH [11]. Preventing PPH-related mortality involves timely identification, access to resources, and skilled healthcare providers. Mitigating risks can be achieved through predictive modeling for anticipating complications and implementing precautionary measures [12], [13].

Machine learning (ML) models, driven by intelligent algorithms, show excellent performance in various domains [14]. In maternal health, ML, a subset of artificial intelligence, holds promise for improving predictions related to PPH. ML doesn't require explicit programming but leverages data on factors contributing to PPH [15]–[17]. Recently, ML algorithms have gained prominence in computer science research, particularly in maternal health. Various ML techniques automatically classify clinical data for disease diagnosis, showing diverse predictive performances [18], [19]. However, deploying ML algorithms in clinical settings poses challenges, including the potential obstacle of overfitting, affecting various prediction models [20]. ML tools with strong nonlinear fitting capabilities can model and analyze PPH. Trained on historical data, these models predict PPH likelihood, assess severity, and forecast outcomes. This aids early detection and intervention by healthcare providers, aiming to reduce PPH-related mortality [21]. To identify pregnant women at risk of PPH, we aim to systematically review existing predictive models. The goal is to evaluate their suitability for current clinical use, enabling accurate and timely PPH risk identification. This review seeks to pinpoint effective models, contributing to refining and implementing existing ones for enhanced early and precise PPH risk detection.

2. METHOD

This study employed a review protocol to guide the selection of articles, following a systematic literature review (SLR) methodology based on the PRISMA method. The SLR process systematically sought out and evaluated previous studies by adhering to a defined set of procedures [22], [23]. This process involved defining sources, criteria, collecting data, and compiling study results.

2.1. Database and search strategy

The literature collection process began by identifying keywords. Four databases were used, applying a seven-year publication filter to gather relevant research articles. This process as outlined in Table 1.

Table 1. Search expression used in the systematic review

Database	Search expression	Year of publication
Scopus, PubMed, Science Direct, IEEE Xplore	*"Postpartum Hemorrhage"* or *"Maternal Bleeding"* and *"Artificial Intelligence"* or *"Machine Learning"*	2017-2023

2.2. Article selection procedure

The process of article selection in the chosen databases was structured into three distinct stages as shown in Figure 1. Stage 1: initial identification of relevant articles by scrutinizing titles and abstracts, eliminating duplicates. Stage 2: selection based on inclusion and exclusion criteria, including English-language original articles, full-text accessibility, publication within the last five years (2017 to 2023), human studies on maternal bleeding and postpartum hemorrhage using artificial intelligent (AI), ML, or deep learning (DL) techniques. Exclusion criteria were also applied: i) systematic reviews and ii) studies without the utilization of AI, ML, or DL methods. Stage 3: qualitative synthesis of the final 43 articles following the application of these criteria.

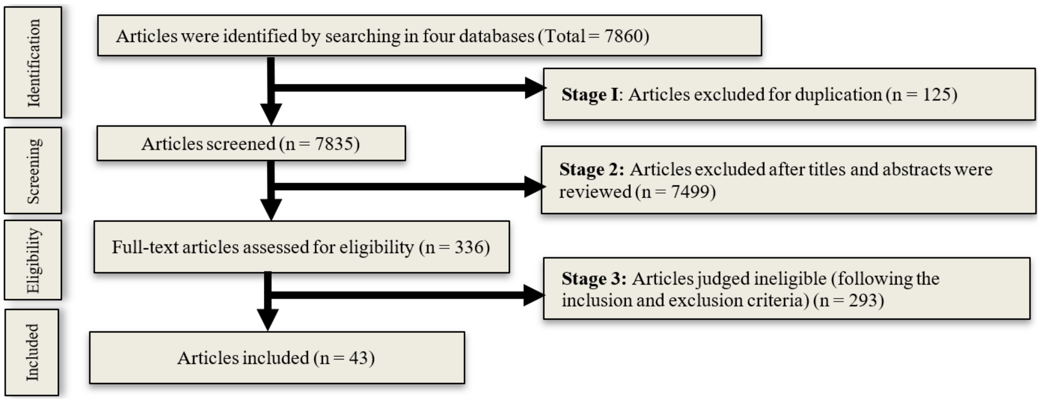

Figure 1. The flow of article selection procedure

3. RESULTS AND DISCUSSION

Out of 7,860 articles identified across 4 databases, 336 were selected after filtering for duplications, journal origin, and completeness. Further criteria, including year, language, and open access, reduced the count to 336. After excluding 293 unrelated research papers, the final result is 43 articles. Accurate prediction of PPH is crucial for effective management, allowing precise identification and stratification of high-risk women.

Despite advancements in PPH treatment, effectively stratifying pregnant women, especially during unexpected massive hemorrhage in vaginal births, remains a clinical challenge. Given PPH's global prevalence and its status as a leading cause of maternal morbidity, identifying and stratifying high-risk women are critical measures in saving maternal lives.

3.1. Characteristics of publication

Examining publication characteristics such as publication year, first author nationality, and research focus is crucial for assessing the quality and relevance of research articles. This evaluation contributes to establishing a robust research foundation, constructing solid arguments, recognizing reliable conclusions, and advancing knowledge within a specific research area, particularly in the context of ML and PPH research. Figure 2 shows the publication years of research articles from 2017 to early 2023, indicating a noticeable increase in the intersection of ML and PPH research. This temporal analysis provides insights into evolving trends and allows researchers to track developments in the field over time.

Figure 3 displays the distribution of research on obstetric risk, emergency maternal care, maternal bleeding, and technology across countries. China leads with 13 articles, followed by the United States with 11. South Korea and Japan contributed 6 each, while Australia contributed 2. Several other countries, including the United Kingdom, Indonesia, South Ethiopia, Italy, Colombia, Nigeria, Zambia, Switzerland, Ireland, Iran, and France, also contributed. This global distribution highlights technology's crucial role in maternal healthcare and its potential for global collaboration in addressing healthcare challenges [24]. here's a noticeable gap in technological adoption between developed and developing nations, often due to bureaucratic processes and administrative efficient [25]. The figure reveals limited research activity in Southeast Asian nations, presenting an opportunity for leveraging technology to enhance healthcare outcomes.

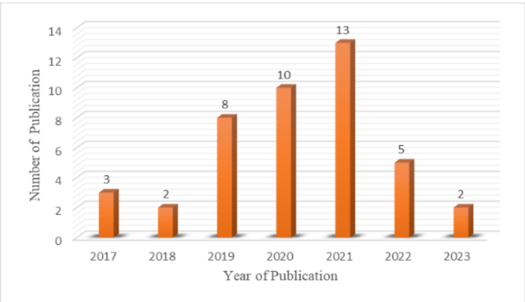

Figure 2. Publication count by year

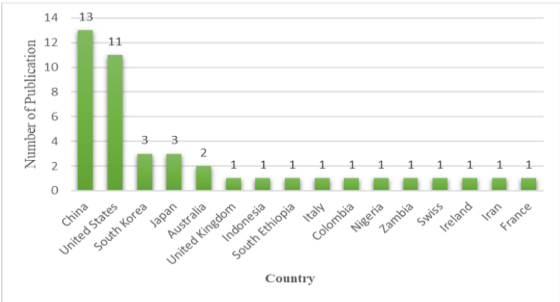

Figure 3. Publication count by countries

Research on emergency maternal care, particularly PPH using AI, shows an upward trajectory, as seen in Table 2. However, only 17 additional articles explore PPH predictions with ML, indicating further research potential in this area. Figures 4 and 5 employ network and density visualizations to depict keyword relationships in article content, defining the research landscape. Key terms such as "postpartum hemorrhage," "predictive model," and "machine learning" dominate, with clinical keywords still prevalent. Figure 6 reveals collaborations among 237 authors in maternal bleeding research, particularly on PPH.

Table 2. Publication count by the research focus and years

Research focus	Years of publication						
	2017	2018	2019	2020	2021	2022	2023
Emergency maternal	-	-	1	-	-	-	-
Maternal bleeding	1	-	2	2	3	1	-
Obstetric risk	1	-	3	5	5	2	-
Postpartum hemorrhage	1	2	3	3	4	2	2
Postpartum complication	-	-	-	-	1	-	-
Amount	3	2	8	10	14	5	2

3.2. Performance of ML methods

Based on findings from selected publications, it is reasonable to conclude that ML has substantial potential for predicting PPH. The integration of ML algorithms in research aims for the most accurate modeling techniques. Performance metrics like accuracy (ACC), area under the curve (AUC), sensitivity (SENS), specificity (SPEC), and standard deviation (SD) assess the results across all selected articles. Within the 43 articles, 17 specifically focus on identifying or detecting PPH, with detailed performance results in Table 3. These metrics are crucial for gauging the effectiveness and reliability of ML models in PPH prediction, contributing to their refinement and optimization for PPH management.

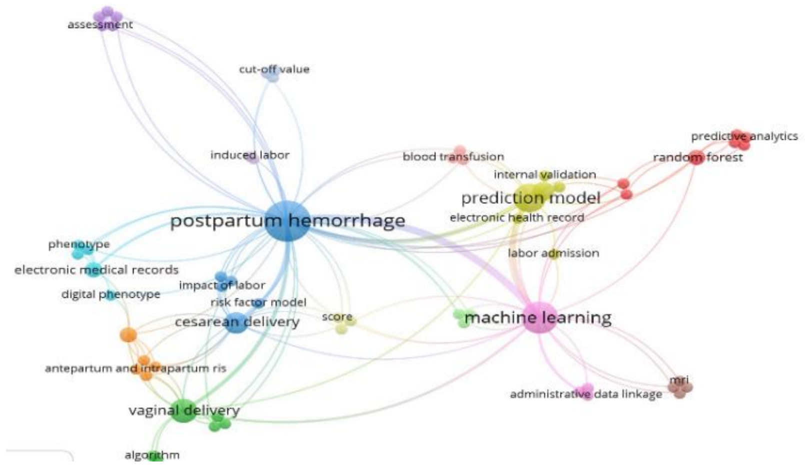

Figure 4. Relationships between the common terms using the bibliometric map

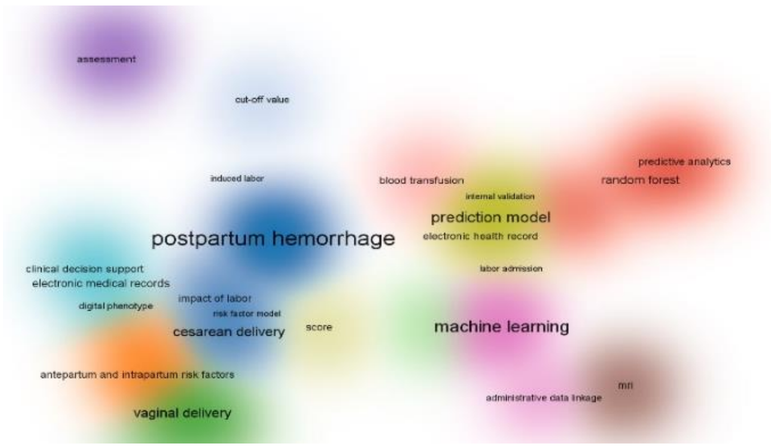

Figure 5. Density visualization of common terms in the selected articles

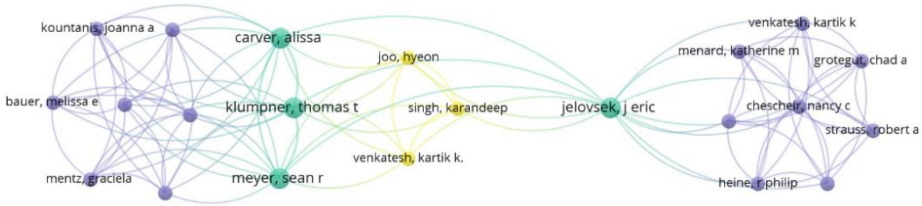

Figure 6. Bibliometric map depicting collaboration relationships among authors and co-authors

In the SLR results, all analyzed articles applied a supervised learning approach for predicting PPH. The majority (n=13) adopted a multi-algorithm approach, aiming for optimal predictive performance. Common ML algorithms for PPH prediction include logistic regression (LR) (n=20), extreme gradient boosting (XGB) (n=8), random forest (RF) (n=4), decision tree (DT) (n=3), and support vector machine (SVM) (n=2). LR has been historically foundational in PPH prediction models [26]-[33]. Ries *et al.* [33] reported LR achieving the highest performance with a 92% accuracy. Shuai *et al.* [34] demonstrated in 2017 that SVM, coupled with a genetic algorithm, outperformed traditional SVM, making it suitable for predicting PPH in pregnant women. Venkantesh *et al.* [35] utilized algorithms, including XGB and RF, in 2020 to develop PPH prediction models, with XGB exhibiting the best performance (AUC of 0.93, 95% CI), followed closely by RF (AUC of 0.92, 95% CI). In contrast, Romeo *et al.* [36] reported k-NN achieving the highest accuracy of 98% in their study.

Akazawa *et al.* [37] found LR as the best-performing model for PPH prediction (accuracy: 69%). Venkatesh *et al.* [35] reported XGB showing superior net benefits across clinical decision thresholds (0% to 80%) and the highest discriminative ability (C statistic: 0.93; 90). Similarly, Malacova *et al.* [38] focused on stillbirth prediction and noted XGB achieving AUC values ranging from 0.59 to 0.84. These AUC values indicate the algorithm's ability to distinguish between live births and stillbirths. However, Betts *et al.* [39] found limited success in PPH forecasting with the XGB model (AUC less than 0.700), attributing it to the use of clinical data and inadequate predictive efficacy across distinct samples. These diverse findings highlight the significance of algorithm selection, dataset characteristics, and model validation in PPH prediction research, emphasizing the need for careful consideration of these factors in future studies.

3.3. Key features and dataset characteristics for PPH prediction with ML

Several of the selected articles emphasize the significance of features exhibiting strong correlations when predicting PPH using ML. These highly correlated features are instrumental in achieving accurate predictions. Table 4 provides an overview of the essential features utilized in those studies, their data sources, and the respective sample sizes. Qi *et al.* [40] used a DT model, finding placenta previa as a primary risk factor associated with a 45.5% chance of 1,000 ml estimated blood loss (EBL) and a 17.5% chance of ≥2,000 ml EBL. Kebede *et al.* [41] experimented with adaptive K-nearest neighbor (AKNN-IF), incorporating factors like uterine inertia and achieving an accuracy of 0.834, outperforming DT, SVM, and traditional K-nearest neighbor (KNN) algorithms. Klumpner *et al.* [42] identified prepartum anemia as a predictor of PPH, (adjusted odds ratio (AOR): 7.4, 95% CI: 3.6, 15.3), with pregnancy complications (AOR: 4.7, 95% CI: 2.2, 10.1) and labor complications (AOR: 1.8, 95% CI: 2.8, 4.2) also playing significant roles. Prepartum anemia was linked to potential primary PPH with minimal blood loss, emphasizing the importance of early identification during antenatal care. Previous clinical research has established correlations between bleeding extent and morphological characteristics like placenta configuration, orientation, or lesion characteristics.

Table 3. Performance of ML methods in PPH study

Author (year)	Methods	Best algorithm	Performance metrics AUC	Acc	Sens	Spec	SD
Huang *et al.* [29]	Multivariable logistic regression (MLR)	MLR	0.87	-	-	-	-
Shuai *et al.* [34]	Pearson correlation coefficient, SVM; radial basis function (RBF)	SVM	-	-	-	-	49.26
Venkatesh *et al.* [35]	LR; LR with lasso; RF; extreme gradiant bossting model (EGMB)	EGBM	-	0.93	-	-	-
Akazawa *et al.* [37]	LR; SVM; RF; 2-layered NN	LR	0.71	0.69	-	-	-
Betts *et al.* [39]	Boosting trees (BT) algorithm	XGB	0.70	-	-	-	-
Qi *et al.* [40]	DT; 5-fold cross validation	DT	-	0.98	-	-	-
Dunkerton *et al.* [43]	C4.5; AKNN-IF; KNN; SVM; DT	AKNN-IF	0.78	0.83	-	-	-
Wu *et al.* [44]	LR with Lasso; SVM	SVM	0.83	68.10	97.60	44	-
Liu *et al*. [45]	Gradient boosting; deep-lab-V3+ network	Deep-Lab-V3+ Network	-	75.61	75	77.46	-
Miyoshi and Khondowe [46]	LR	LR	-	-	19	92.30	-
Chen and Xu [47]	The self-adaptive edge detection algorithm	SAEDA	-	94.44	-	-	-
Goad *et al.* [48]	LR	LR	0.81	-	86.90	74.20	-
Zhang *et al.* [49]	Ensembling learning (RF, GBDT, XGB, SVM), artificial neural network (ANN)	GBDT	-	96.70	-	-	-
Westcott *et al.* [50]	LR; RF; XGB; SVM; DT	XGB	0.98	98.10	0.74	-	-
Liu *et al.* [51]	KNN and RF; K KNN; light-gbm and LR, LR	Light-gbm +LR	0.73	-	0.69	0.80	-
Bihan *et al.* [52]	MLR	MLR	0.69	-	-	-	-
Mehrnoush *et al.* [53]	Adaptive syntetic; LR; DT classifier; RF; XGB; permutation classification; feed forward deep learning; light GBM (LGB); SVM	XGB classification	-	0.98	-	-	-

PPH data predominantly come from hospital settings, offering comprehensive medical records, trained healthcare professionals, and controlled childbirth environments for meticulous documentation. Hospitals facilitate multidisciplinary care teams for effective PPH management. Dunkerton *et al.* [43] reported an automated system detecting PPH cases missed by existing surveillance criteria, suggesting integration with nursing-driven early warning systems for improved detection. Sample sizes varied from 36 to 361,332, with limitations such as small datasets for ML models and lack of external validation. Future research should prioritize big data analysis with high-quality variables to enhance PPH prediction model accuracy.

Table 4. Importance features, data sources, and sample size

Author (year)	Important features	Data source	Sample size
Huang *et al.* [29]	Maternal complication, bleeding score; antepartum platelet transfusion; placental abnormalities; platelet count; previous uterine surgery; primipara.	18 academic tertiary centers in China	677
Shuai *et al.* [34]	2 hours postpartum blood pressure-high; pregnancy times; mode of delivery; delivery day; 2 hours postpartum blood pressure.	Gulou Hospital Nanjing	5,036
Venkatesh *et al.* [35]	Pregnancy weight; admission weight; macrosomia; temperature; trial of labor; maternal BMI; systolic blood pressure; multiple gestations; anemia during pregnancy; admission spontaneous labor.	Eunice Kennedy Shiver National Institute of Child Health, USA	228,438
Akazawa *et al.* [37]	Pregnant gestation of labor; admission maternal weight; maternal weight before pregnancy; age; maternal height; birth weight; parity; delivery mode; sex of baby; labor induction; fetal position.	Tokyo Women Medical University East Center	9,894
Betts *et al.* [39]	Maternal BMI; maternal height; administration of packed blood cells; cesarean delivery; allied health intervention; management of PPH; gestational weeks at delivery; medical practitioner; birth length; birth head circumference; maternal age; other condition complicating pregnancy; multiple deliveries; maternal weight; local hospital area code; retained placenta; PP manual exploration.	Administrative records of all live births in Queensland	361,332
Qi *et al.* [40]	Uterine inertia; soft birth canal injuries; placental factors; coagulation disorder.	Hospital of Nanjing Medical University	1,829
Dunkerton *et al.* [43]	Placenta previa; previous cesarean section.	Hadassah Medical Center Obstetric Department	24,230
Wu *et al.* [44]	Maternal age; gravidity; parturition; abortion; previous cesarean delivery (CD), hemoglobin value before CD; vaginal bleeding; gestational age (GA) at magnetic resonance imaging (MRI) weeks; GA delivery; pregnancy complication; ultrasound placenta previa, ultrasound placenta accrete spectrum (PAS); CD; estimated blood loss; blood transfusion; final diagnose PAS.	Henan Provincial People's Hospital and the Hospital of Zhengzhou University	207
Liu *et al.* [45]	Gray level co-occurrence matrix (GLCM) correlation; gray level size zone matrix (GLSZM), GLCM inverse variance, gray level run length matrix (GLRLM) run entropy, gray level dependence matrix (GLDM), small dependence high gray level emphasis.	First Affiliated Hospital of Nanchang University	210
Miyoshi and Khondowe [46]	Vaginal deliveries; para ≥7; parity-cut-off values of 1-2, a cesarean section at the current pregnancy; birth weights.	University Teaching Hospital, Lusaka Zambia	1,704
Chen and Xu [47]	Age; GA; parity; cesarean section; complete placenta previa; represent the partial represents placenta previa; marginal placenta previa; hysterectomy.	Changsha Hospital, Hunan Province, China	36
Goad *et al.* [48]	Maternal age; history of PPH; BMI; history of cesarean delivery; gestational hypertension; abnormal placental; spontaneous vaginal delivery; labor duration; delivery complication; outborn and precipitated delivery.	Denver Health Medical Centre	10,029
Zhang *et al.* [49]	Present gestation; factors related to delivery; factors related to delivery; factors related to delivery.	The Beijing Obstetrics and Gynecology	3,500
Westcott *et al.* [50]	Mode of delivery.	NYU Langone Health Tisch Hospital	30,867
Liu *et al.* [51]	Haematocrit; shox index; contraction frequency; white blood cell count; hypertensive disorder; baby weight; second stage duration; mean area of contractions; total amnion fluid after delivery; BMI.	HER e-health data from the First Affiliated Hospital of Jinan University	10,520
Bihan *et al.* [52]	Pre-eclampsia; antepartum bleeding; multiple pregnancy; macrosomia and labor duration ≥8.	Brest Univerity Hospital, France	2,742
Mehrnoush *et al.* [53]	Parity; education; living residence; induced labor; CD.	Khaleej-eFars Hospital, Iran	8,888

4. CONCLUSION

Global concerns about PPH necessitate effective prediction methods for the well-being of pregnant mothers and fetuses. ML emerges as a promising AI approach for PPH prediction, aiding in the accurate selection and stratification of high-risk women. Through a SLR, 43 articles were identified, with 17 specifically addressing PPH prediction using ML. ML algorithms, including LR, DT, RF, and XGB, show promise for early detection of PPH. The importance of algorithm selection, dataset characteristics, and model validation is underscored, emphasizing the need for careful consideration in future research. ML's potential in enhancing PPH prediction is evident, with several studies highlighting the significance of features exhibiting strong correlations in predicting PPH using ML.

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