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RESEARCH **Open Access**

Machine Learning-based Prediction Model for Adverse Pregnancy Outcomes: A Systematic Literature Review

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Abstract
Most of Adverse Pregnancy Outcomes (APO) are preventable particularly if the health personnel can early detect the risk. This study aimed to review articles on how the machine learning model can predict APO for early detection to prevent neonatal mortality. We conducted a systematic literature review by analyzing seven articles which published between 1 January 2013 and 31 October 2022. The search strategy was the populations are pregnant women, intervention using machine learning for APO prediction, and the outcomes of APO are Low Birth Weight, preterm birth, and stillbirth. We found that the predictors of LBW were demographic, maternal, environmental, fetus characteristics, and obstetric factors. The predictors of preterm birth were demographics and lifestyle. Meanwhile, the predictors of stillbirth were demographic, lifestyle, maternal, obstetric, and fetus characteristics. It was indicated that Random Forest (Accuracy: 91.60; AUC-ROC: 96.80), Extreme Gradient Boosting (Accuracy: 90.80; AUC-ROC: 95.90), logistic regression (accuracy 90.24% and precision 87.6%) can be used to predict the risk of APO. By using a machine learning algorithm, the best APO prediction models that can be used are logistic regression, random forest, and extreme gradient boosting with sensitivity values and AUC of almost 100%. Demographic factors are the main risk factors for APO.

Keywords: Adverse, Pregnancy Outcome, Prediction, Model, Machine Learning.

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1. INTRODUCTION

In 2020, 2.4 million neonatal deaths, which are defined as deaths that occur during the first 28 days of life, were recorded globally (WHO, 2022). The high rate of neonatal and under-five mortality has led to the inclusion of this issue into the Sustainable Development Goals (SDGs), where one of its goals is to end the preventable neonatal and under-five mortality in 2030, which countries are expected to be able to decrease neonatal mortality rate to 12 per 1,000 live births in the same year (Bappenas (National Planning Board), 2024).

The first month of life is crucial for a child's survival. Most neonatal deaths during this period are linked to maternal factors, that are preventable, such as preterm birth complications, birth complications (asphyxia), and maternal infections causing stillbirth. A previous study also includes low birth weight as the main predictor of neonatal mortality (Tadese et al., 2022). These causes are parts of the Adverse Pregnancy Outcomes (APO).

Adverse pregnancy outcomes are considered to be the main cause of morbidity and mortality among mothers and babies, affecting both the physical and mental aspects, and particularly occur in low- and middle-income countries in Asia and Africa. In terms of neonatal mortality, Indonesia ranks seventh among countries with high neonatal mortality rates worldwide and ranks first in Southeast Asia. The Indonesian Demography Health Survey (IDHS) demonstrates that the trend of neonatal mortality in Indonesia tends to be stagnant from 2002 to 2017 (National Population and Family Planning Board (BKKBN); Stastistics Central Bureau (BPS); Ministry of Health; USAID, 2017). Low birth weight (34.5%) has been identified as the main cause of neonatal mortality in Indonesia, followed by preterm birth (22.5%), congenital abnormality (11.4%), and infection/sepsis (3.4%) (Indonesia Ministry of Health (Kemenkes RI, 2022).

Some factors may contribute to Adverse Pregnancy Outcomes, including obstetric, maternal, lifestyle, and sociodemographic factors. Since APO is the primary cause of neonatal deaths, it is beneficial to develop procedures that accurately predict the possibility of APO, especially preterm birth, stillbirth, and low birth weight, to avoid neonatal mortality (Mombo-Ngoma et al., 2016; Younger et al., 2022). Several statistical methods and Artificial Intelligence (AI) can predict APO risk factors, one of which is Machine Learning which is used to provide accurate predictions. This research aims to collect and review articles on how machine learning models can predict adverse pregnancy outcomes for early detection to prevent and reduce neonatal mortality.

2. RESEARCH METHOD

This study conducted a Systematic Literature Review (SLR) using Perish for article search, Microsoft Excel (licensed) for inclusion and extraction, and VOSviewer for comparative analysis. The six steps followed were: defining the research question, determining study characteristics, finding relevant articles, choosing articles that meet criteria, synthesizing information, and reporting results. VOSviewer was used to visualize the results of the comparative analysis.

Study Criteria

All articles reviewed in this study discuss the machine learning model used to identify and predict Adverse Pregnancy Outcomes.

Search Strategy

The authors used PICOS to identify articles that meet the inclusion criteria of the study. The topic for PICOS was: P: Pregnant Outcomes OR Low Birth Stillbirth OR Preterm birth, I: Risk Factor, C: Algorithm Machine Learning, O: Accuracy OR ROC OR AUC. We included articles written in English and published between 1st January 2014 and 31st Desember 2023. This was followed by identifying relevant sources using Pubmed, Proquest, Embase, and Scopus databases. The keywords or synonyms used were "Pregnant Outcomes" OR "Low Birth" OR "Stillbirth" OR "Preterm birth" AND "Risk Factor" AND "Machine

Learning" AND "Accuracy" OR "ROC" OR "AUC". PRISMA was then applied to determine whether the articles were relevant to the topic or not.

Study Article Selection

We screened 180 articles for inclusion in the study. After removing duplicates and non-eligible articles, we ended up with seven articles that met the study's inclusion criteria and were included in the analysis.

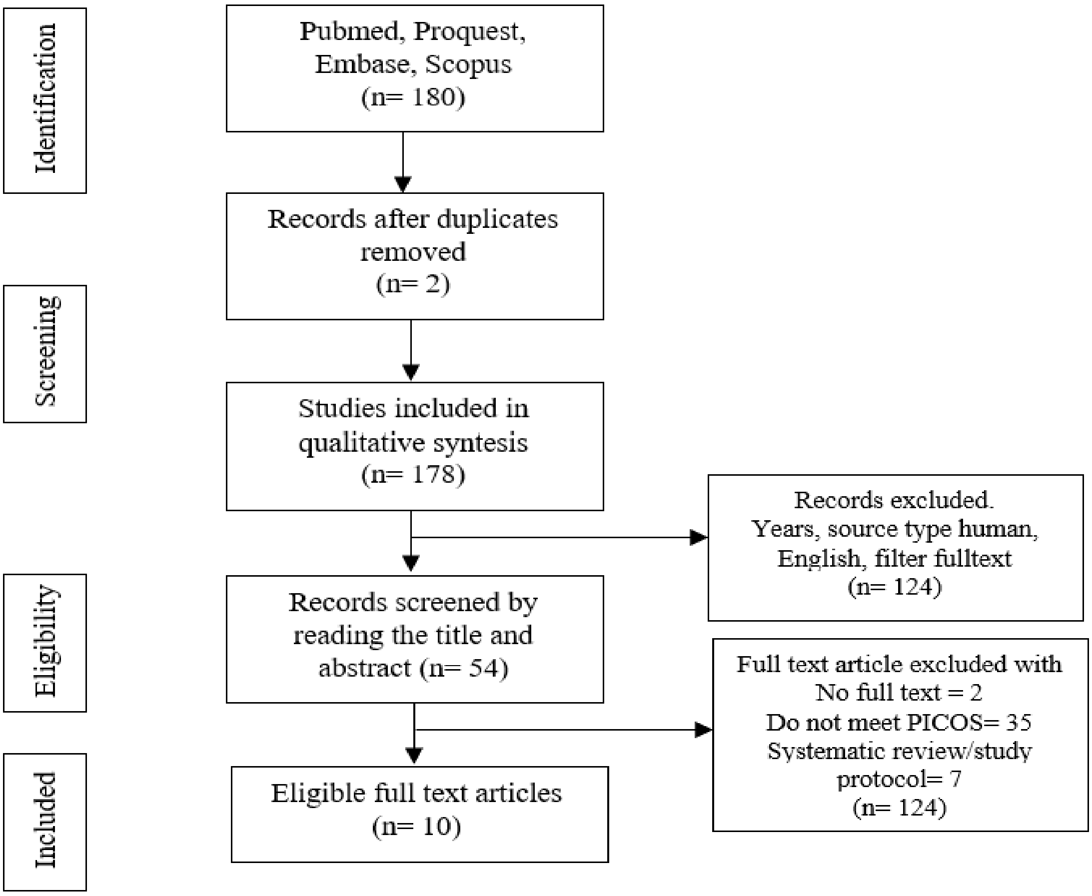

Figure 1. Article selection process using PRISMA SLR

Data Analysis

The authors collected data on respondent characteristics, data type, research design, sample, and results from articles in their study. Adverse Pregnancy Outcome (APO) was classified into three categories: Low birth weight, Stillbirth, and preterm birth. Machine learning techniques such as Random Forest, Decision Tree, Naïve Bayes, Logistic Regression, K-Nearest Neighbor, etc. were used to identify APO risk factors with a focus on ROC and AUC values above 0.7.

Ethical Clearance

As this study used the Systematic Literature Review approach and did not directly affect human, no ethical clearance was needed.

3. RESULTS AND DISCUSSION

Articles included in this study were published in the last 3 years. The duration of study presented in the articles was varied with the shortest being 5 months and the longest being 4 years. The location of the study described in these articles included America, East Asia (China), Australia, South Asia, South Africa, East Africa, and Central Europe. Studies described in the articles used the prospective and retrospective cohort design with most data sets from data recorded in demographic and national health surveys or hospital data records.

The risk factors for Adverse Pregnancy Outcomes are categorized into six main factors: socio-demographic, general morbidity episodic illness, infections and environment, behavior, history of smoking, infant characteristics, and obstetrics. Among these, socio-demographic factors are identified as the main predictor (Mombo-Ngoma et al., 2016). This categorization provides a clear overview of the main factors influencing the incidence of APO.

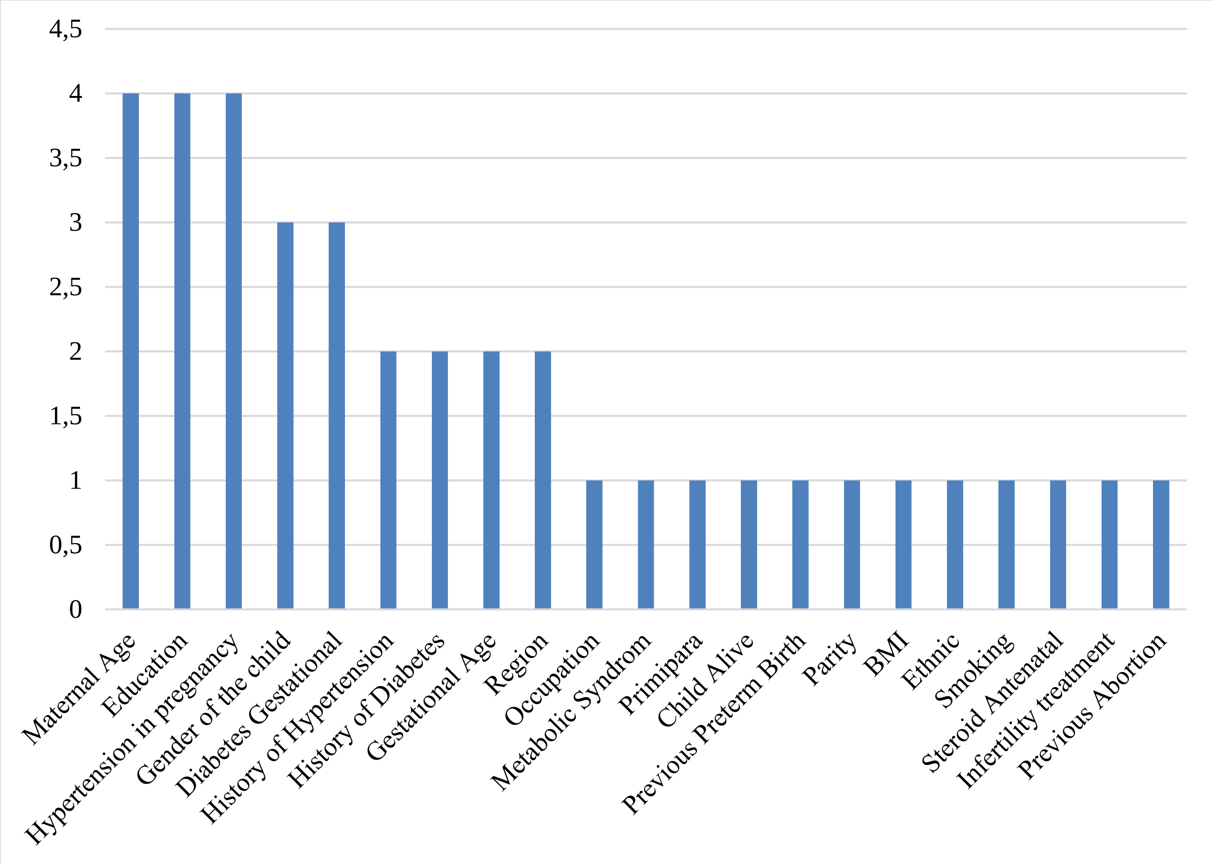

Figure 2. Frequency of Predictors for Adverse Pregnancy Outcomes

Prediction Modeling of Adverse Pregnancy Outcomes Using Machine Learning Algorithm

The research studies used various machine learning models to identify risk factors for Low Birth Weight (LBW) and preterm birth (Bekele, 2022b). Cho et al. and Bekele conducted studies using multiple modeling approaches, such as random forest, decision trees, k-nearest neighbors, support vector machines, Xgboost, and Naïve Bayes (Wang et al., 2016). Pollob et al. and Khan et al. also explored risk factors for LBW using different models (Ashikul Islam Pollob et al., 2022). Belaghi, Beyene, and McDonald used logistic regression, random forest, Artificial Neural Networks, and Decision Tree to predict risk factors for preterm birth (Chen et al., 2023). Zhang et al. used Extreme Gradient Boosting and long short-term memory models for the same purpose.

A similar study was conducted by Koive and Sairanen (2020) using logistic regression modeling (AUC: 0.64), artificial neural network (AUC: 0.66), and gradient boosting decision tree (AUC: 0.67) to determine the risk factors for preterm birth. The same modeling approach was also carried out by Koivu and Sairanen (2020) to determine the risk of early stillbirth with logistic regression (AUC: 0.74), artificial neural network (AUC: 0.74), gradient boosting decision tree (AUC: 0, 76). As for APO late stillbirth with logistic regression (AUC: 0.61), artificial neural network (AUC: 0.57), and gradient boosting decision tree (AUC: 0.61) (Edwards et al., 2021).

The most frequently used algorithm models of machine learning in the ten articles under study are logistic regression, random forest, extreme gradient boosting, naïve Bayes, and K-Nearest Neighbor. The following visualization was obtained using the keywords adverse, pregnancy outcome, prediction, model, and machine learning (Figure 3).

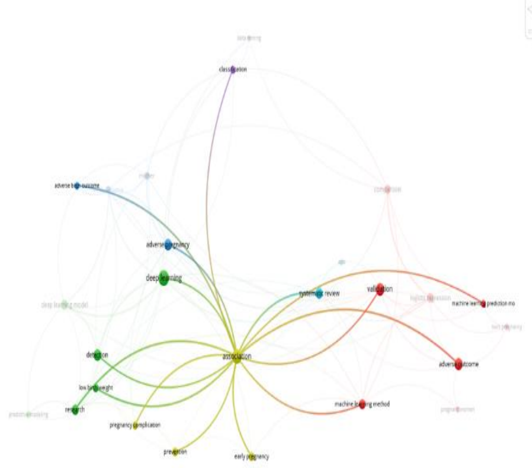

Figure 3. Visualization of keyword

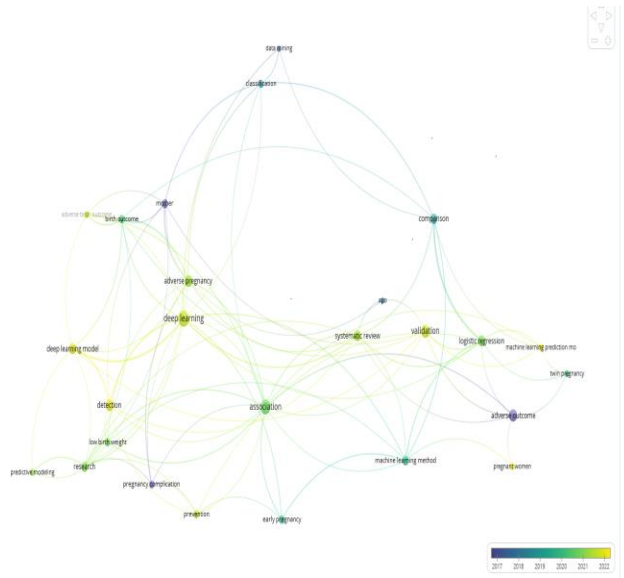

Figure 4. The model used for adverse pregnancy

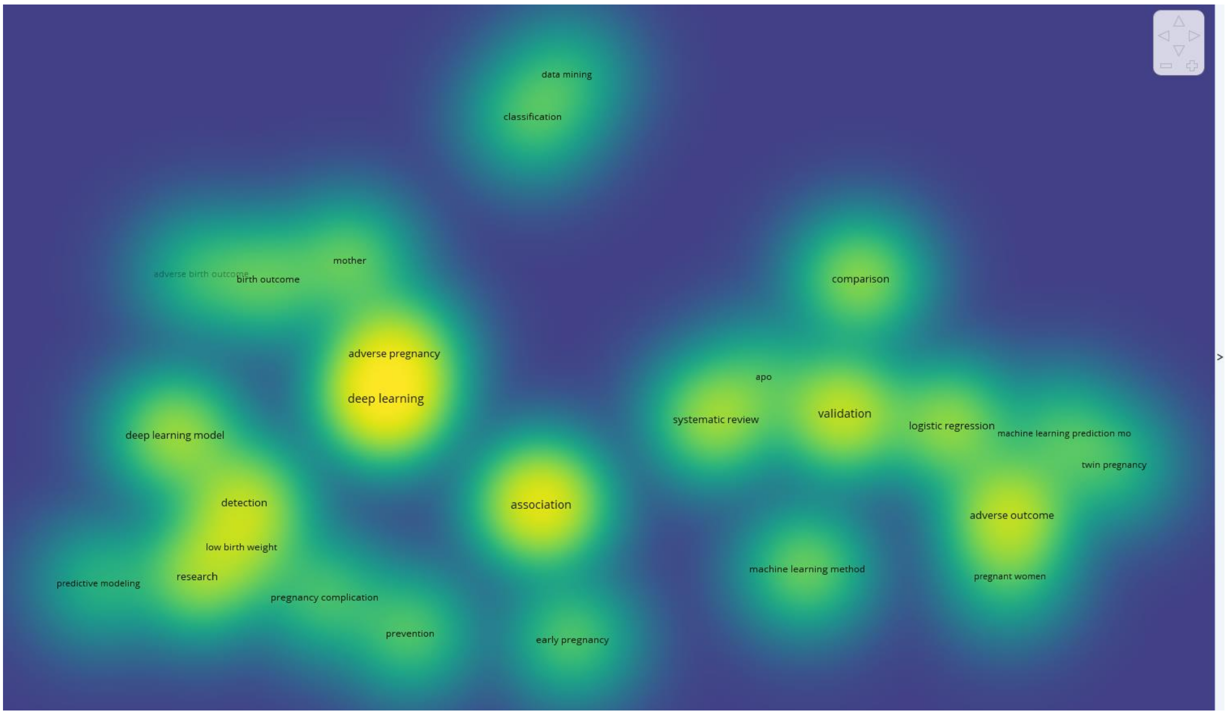

Figure 5. Relationship adverse pregnancy and machine learning method

Adverse Pregnancy is strongly linked to deep learning, machine learning methods, and logistic regression. These methods are frequently used to predict APO (Figure 4). Figure 5 described new study in 2022 discusses the relationship between deep learning, machine learning, and adverse pregnancy. Before 2022, logistic regression was the main model used for adverse pregnancy, but the shift to machine learning and deep learning has occurred due to the development of machine learning models. Adverse pregnancy also has a strong association with detection, early pregnancy, and low birth weight.

Assessment of Adverse Pregnancy Outcome Predictive Modeling

The text discusses how machine learning algorithms were used in studies to identify predictive factors for adverse pregnancy outcomes such as low birth weight, preterm birth, and stillbirth (Belaghi, Beyene, & McDonald, 2021a; B. Zhang et al., 2019). The studies found that socio-demographic factors such as age, education, place of residence, occupation, primiparous, number of live children, parity, BMI, and maternal race were important risk factors (Ashikul Islam Pollob et al., 2022; Khan, Zaki, Masud, Ahmad, Ali, Ali, et al., 2022; Mangold et al., 2021). The studies suggest that logistic regression and random forest are the best modeling approaches for predicting these risk factors.

A study by Bekele (2022) found that mothers under 18 have a 44.9% higher incidence of low birth weight (LBW) babies. Maternal age is a crucial LBW risk factor, along with area of residence, occupation, education, wealth index, and behavior during pregnancy (Endalamaw et al., 2018). Other risk factors include chorioamnionitis, history of the disease, and pregnancy with steroids (Kassaw et al., 2021). Preterm birth is influenced by metabolic syndromes such as blood pressure, uric acid, blood sugar, and lipids, as well as the history of previous preterm birth, age, education, history of smoking, history of hypertension, and infertility treatment (Belaghi, Beyene, & McDonald, 2021a; Puspitasari et al., 2020). Machine learning models such as logistic regression, artificial neural networks, and extreme gradient boosting show strong predictive capabilities for preterm birth and stillbirth risks (Gao et al., 2019).

Table 2. Machine learning in Predicting Adverse Pregnancy Outcomes

Authors	**Adverse Pregnancy Outcomes**	**Model Analysis**	**Accuracy, validation, precision, and Sensitivity**	**Features Included**
(Bai et al., 2022)	Gestational age less than 28 weeks, gestational age less than 26 weeks, birth weight less than 1000 g, birth weight less than 750 g, and small-for-gestational-age	Artificial neural network, the decision tree, the logistic regression, Naïve Bayes, the random forest, and the support vector machine were used for predicting preterm birth	The random forest had the best performance (accuracy 0.79, area under the receiver-operating-characteristic curve 0.72). R-Studio 1.3.959	maternal age (0.2131), birth-month (0.0767), PM10 month (0.0656), sex (0.0428), number of fetuses (0.0424), primipara (0.0395), maternal education (0.0352), pregnancy-induced hypertension (0.0347), chorioamnionitis (0.0336) and antenatal steroid (0.0318
(Arayeshgari et al., 2023a; Ashikul Islam Pollob et al., 2022b; W. T. Bekele, 2022b; Khan, Zaki, Masud, Ahmad, Ali, Ali, et al., 2022b)	Low birth weight	Logistic Regression, Decision Tree (Arayeshgari et al., 2023; Bekele, 2022a; Pollob et al., 2022), used too Random Forest (RF) and support vector machine (Arayeshgari et al., 2023; Bekele, 2022c). Artificial neural network (Arayeshgari et al., 2023) Naive Bayes, K-Nearest Neighbor, , Support Vector Machine, Gradient Boosting, and Extreme Gradient Boosting (Bekele, 2022c) and	91.60 persen accuracy, 91.60 persen Recall, 96.80 percent ROC-AUC, 91.60 percent F1 Score, 1.05 percent Hamming loss, and 81.86 percent Jaccard score (Bekele, 2022c). The logistic regression-based classifier performed: with 87.6% accuracy and 0.59 area under the curve for holdout (90:10) cross-validation (Pollob et al., 2022). The accuracy of all models was 87%. Sensitivity 74%,	Gender of the child, marriage to birth interval, mother’s occupation, and mother’s age (Bekele, 2022c). Region, education, wealth index, weight, height, twin child, child alive, and delivery by CS (Pollob et al., 2022). Gestational age, number of abortions, gravida, consanguinity-ity, maternal age at delivery, and neonatal sex (Arayeshgari et al., 2023) and Diabetes, gestational age, and hypertension

		Absolute error and mean absolute percent error were used for BW estimation (Khan, Zaki, Masud, Ahmad, Ali, & Ahmed, 2022)	specificity 89%, positive likelihood ratio 7.04%,, negative likelihood ratio 29% and ac- curacy 88% (Arayeshgari et al., 2023). The logistic Regression (LR) classifier with 100% oversampling using SMOTE achieved the best classification. performance. accuracy (90.24%), precision (87.6%), recall (90.2%), and F1 (0.89) (Khan, Zaki, Masud, Ahmad, Ali, & Ahmed, 2022).	(Khan, Zaki, Masud, Ahmad, Ali, & Ahmed, 2022)
(Belaghi et al., 2021a) (Zhang et al., 2022) (Sun et al., 2022).	Preterm Birth	Regresi logistic and Machine Learning (Belaghi, Beyene, & McDonald, 2021c). Long short-term memory (LSTM) networks, Time-Series Technology (Y. Zhang et al., 2022). Naive Bayesian (NBM), Support Vector Machine (SVM), Random forest (RF), artificial neural networks (ANN), K-means, and logistic regression (Sun et al., 2022)	AUC increased from 65% (95% CI: 63–66%) to 80% (95% CI: 79–81%) with the inclusion of complications during pregnancy (Belaghi, Beyene, Mcdonald, et al., 2021). LSTM: Accuracy was 0.739, sensitivity was 0.407, specificity was 0.982, and the AUC was 0.651 (Y. Zhang et al., 2022) and RF model was the highest compared with other algorithms (accuracy: 0.816; AUC 0.885, 95% confidence	Abortions (including miscarriages) as the most important predictor of PTB during the first trimester (importance: 28.23 for previous abortions (including miscarriages) vs. 7.79 for diabetes). complications during pregnancy and hypertensive disorders (Belaghi, Beyene, & McDonald, 2021c). Blood pressure, blood glucose, lipids, uric acid, and other metabolic factors (Y. Zhang et al., 2022). Age, magnesium,

			interval (CI): 0.873–0.897) (Sun et al., 2022)	fundal height, serum inorganic phosphorus, mean platelet volume, waist size, total cholesterol, triglycerides, globulins, and total bilirubin (Sun et al., 2022).
(Khatibi et al., 2021)	Stillbirth	decision tree, Gradient boosting classifier, logistics regression, random forest, and support vector machines	Accuracy of 90%, sensitivity of 91%, specificity of 88%. AUC of ±95%, CI of 90.51% ±1.08 and 90% ±1.12	Maternal demographic features, clinical history, fetal properties, delivery descriptors, environmental features, healthcare service provider descriptors, and socio-demographic features
(Koivu & Sairanen, 2020)	Stillbirth and preterm pregnancies	Logistic regression, artificial neural network, and gradient-boosting decision tree	0.76 AUC for early stillbirth, 0.63 for late stillbirth, and 0.64 for preterm birth	Age and BMI, previous pregnancies with adverse effects, various comorbidities, and having an ART pregnancy

4. CONCLUSION

According to the ten articles reviewed in this study, the best APO prediction models that use machine learning algorithms use logistic regression, random forest, and extreme gradient boosting with sensitivity values and AUC of almost 100%. These machine learning models conclude that the risk factors for Adverse Pregnancy Outcomes are mostly socio-demographic, including maternal age, education, occupation, wealth index, area of residence, number of children, and primiparous. Other factors that are also identified as influencing the APO are hypertension, metabolic syndrome (gout, blood pressure, blood sugar, and lipids), diabetes, pregnancy with steroids, history of smoking, history of preterm, multiple pregnancies, weight, and height.

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