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Predicting Premature Birth During Pregnancy Using Machine Learning: A Systematic Review

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Abstract*:* Artificial intelligence is widely developed in the health sector, and machine learning has been increasingly used in healthcare to make predictions, assign diagnoses and as a method of prioritizing actions. machine learning methods have become a feature of several tools in the field of obstetrics and child care. Is to identify the applicability and performance of machine learning methods used to identify preterm labor during pregnancy the main precision metric used is the AUC. the machine learning method with the best results was the prediction of prematurity the SVM classifier algorithm method is the best method for predicting the incidence of premature birth with an accuracy level of 0.997, recall of 0.995, and specificity of 1.0, for identifying a diagnosis of premature birth which is quite good. good. accurately. These results are similar to the results of Rawashdeh et al.'s research on a data mining-based intelligence system using the Naïve Bayes, Decision Tree, K-NN, RF, And NN algorithms with results obtained with an accuracy of 0.95, recall of 1.0, and specificity of 0.94 using rf. To prevent preterm birth, it is critical to support research in this area and develop machine learning-based solutions with broad clinical applicability. It is also advised that future research compare ml with a traditional approach using the same data to comprehend its value in filling the current gap. This comprehensive review makes a substantial contribution to the specialized literature on women's health and artificial intelligence.

Keywords: *Artificial Intelligence, Machine Learning, Maternal, Pregnancy, Preterm Birth*

1. Introduction

The World Health Organization (WHO) describes a preterm birth (PTB) as one where a baby is born before the 37th week of gestation, a term birth occurs between the 37th and 42nd week of pregnancy, whereas births after the 42nd week are referred to as post-term. [1] PTB is a global public health problem that kills approximately 15 million children worldwide [2,3].

Based on global data, the highest number of deaths occurred between the was 0 and he was 4 years old [4]. Various types of clinical, biological, social, and economic risk factors may contribute to complex interactions during pregnancy [5]. According to UNICEF, primary prevention and interventions aimed at reducing the risk of preterm or known birth are attractive to all women [6]. In high-income countries, declines in early mortality are largely underpinned by changes in quality and adequate care policies [7].

According to Basic Health Research, the under-5 mortality rate reached 28,158 in Indonesia. Of these, 20,266 were under 5 years of age (71.97%) and 5,386 (19.13%) died between 29 days and 11 months of age [8]. Based on data at the General Hospital dr. H. M. Ansari Saleh Banjarmasin which is a referral hospital, the incidence and number of PTB cases have increased based on a preliminary study conducted in the last three years, the incidence of PTB in 2017 was 251 (8.34%) out of 3,007 mothers who gave birth. gave birth, in 2018 there were 285 (10.16%) cases from 2,804 mothers who gave birth and this increased again in 2019 to 237 (13.07) %) from 1,813 mothers who gave birth. Data shows an increase in PTB cases in Dr. H.M Ansari Saleh Banjarmasin every year [9].

Breakthrough efforts have been made in Indonesia to overcome the PTB problem. One of them is Birth Planning and Prevention of Complications (P4K) in the Guidelines for Care for Pregnant Women (KIA) which focuses on the role of the family and community in care and early detection by preventing health risks and providing access to health facilities for pregnant women. pregnant women [10]. Identification of appropriate risk factors for predicting PTB is a determinant for the prevention of PTB events and the quality of subsequent infant care [11]. Therefore, the initial stage of identifying PTB risk factors is a complex task because multifactor variations, population characteristics, and PTB phenomena greatly influence the detection of PTB [12]. In a cohort study and systematic review, it was shown that the PTB prediction model with an accuracy rate of 78% occurred in nulliparous women [13].

PTB prediction research in the medical field is currently being developed, as an effort to reduce the incidence of

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prematurity which cannot be predicted accurately [14,15]. Several studies on PTB prediction using AI and ML have been carried out, for example in Indonesia [6] [16], [17], namely on electro hysterographic signals, electronic medical records, and transvaginal ultrasound. This study uses an AI and ML algorithmic method approach in addressing the clinical challenges of PTB prevention to find a predictive model for the risk of delivery. [18], [19]Data-driven prediction of pregnancy complications was identified as the most commonly used technique from AI models to assess the effectiveness of artificial intelligence-based technological models in medicine [20], [21] [22], [23], Other studies such as predictive models use ML and DL together to detect early PTB risk factors [25] [26] The application used is a medical application using ML because the machine learning method has an important role in predicting disease, given the amount of data generated by the health nursing industry using statistical methods. The results showed that the ML approach has the best performance with the highest accuracy of 0.89 (89%) on PBS monitor technology which provides accuracy, with AUC values of 0.888, 0.780 and 0.897. Modeling very preterm births using the DL model also provides consideration of temporal relationships in electronic medical records. The ML model showed better predictive performance than the traditional logistic regression model, in this model the best results combined information about maternal physical characteristics and habits during pregnancy with a sensitivity of 91.4% and a specificity of 99%. [19], [24] Another prediction model was built based on maternal characteristics, obstetric history, gynecological history, cervical characteristics, number of fetuses, presence or absence of symptoms, type and time of binding, and progesterone supplementation. In the first model, the RF classification obtained the best classification results in terms of G-mean and sensitivity with values of 0.96 and 1.00 respectively at 200% oversampling level.On the other hand, findings indicate that the main risk factors for PTB can be predicted using input factors such as maternal height and number of pregnancies using computational techniques such as SoftMax regression with NN with PLO optimizer to train the prediction model. The success rate obtained is 89.99% [25]. Another study used risk assessment stratification using six ML algorithms with RMSE index results with lower RMSE values obtained by an estimated gestational age at birth of 2.09 95% IC (2.090-2.097). with the Extreme Gradient Enhancement approach.

Based on this problem, this study focuses on the use of ML techniques to identify features of PTB during pregnancy based on medical records and identify potential risk factors for preterm labour in pregnant women. The goal is to develop a predictive model that can accurately identify women at risk of preterm delivery in the early stages of pregnancy, enabling earlier intervention and better outcomes for mother and child. Data will be collected from a large number of pregnant women, and various machine learning algorithms will be applied to that data to identify patterns and relationships that can be used to predict preterm birth. Model performance will be evaluated using various metrics, such as accuracy, sensitivity, and specificity. The results of this study will provide a valuable contribution regarding the use of AI and ML to predict PTB during pregnancy [1]

2. Methodology

2.1. Information Sources

Methodological research was conducted by utilizing four databases, namely Science Direct, Scopus, springer, IEEE, and PubMed, the articles were chosen because based on a number on a number of inclusion criteria related to the topic under investigation. Articles taken from publication 2018 to 2022 and the type of publication is journal and conference proceeding. The publication language English, the scope publication is full text and the type of field about artificial intelligentsia, machine learning, deep learning, Preterm birth, and pregnancy were used as inclusion criteria.

2.2. Selection of Study

The systematic review in this article follows the principles used in the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA). The PRISMA SLR protocol for preterm birth is depicted in Figure 1. The article search procedure was applied to all approved databases by entering relevant data. The source of the query search comes from the database, the search procedure is performed by entering keywords as search strings, such as ("Preterm Birth" AND (“Prediction” OR “Classification”)" AND "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") displays the query text. Advanced search options are used in all database engines to access journals and conference papers.

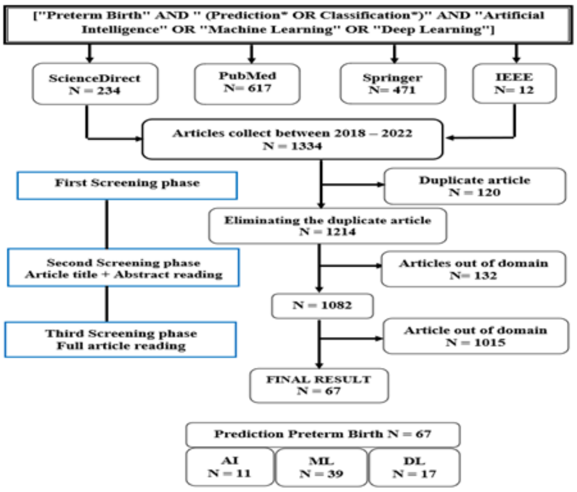

Fig 1. Systematic Reviews modelling studies

2.3. Eligibility Criteria

The main research areas identified are PTB Prediction, disease prediction, and classification by AI, ML, and DL. The classification stage is separated into three parts. The first is the Screening stage by eliminating the same article. The second screening stage is to determine the title and abstract of the article based on the research domain. The last stage is to read all articles and eliminate them if they are outside the research domain.

2.4. Data Collection Procedure

Important indicators and comments were identified after reviewing the full text of articles and categorizing them under a refined classification. All comments were then placed on these texts. The main results were summarized and described. Specific items, such as summary tables, targets, verification criteria, description, source index, and data set, were used to save relevant information. Word and Excel documents were used.

2.5. Search Result and Literature Taxonomy

The initial results of research searches related to the topic include 1334 articles, 234 of which are from the ScienceDirect index, 617 from the PubMed index, 471 from the Springer index, and 12 from the IEEE Explore index. These articles were published over a 5-year period from 2018 to 2022. Then, the screening stage is divided into three parts; the first stage is to remove articles with duplicates. One hundred and twenty articles had duplicates and the remaining 1214 articles. The second stage is to select articles by reading the whole abstract and eliminating titles outside the domain; the result is one hundred forty-seven articles and the remaining 1082. The last stage is to choose based on reading the entire article's content and eliminate outside domains; the result was finally collected thousand and ten articles and the remaining 67. The results of 67 articles studied extensively map the research area. The research map is determined based on the type of PTB, then entered into the method, modeling application, and finally, the algorithm that produces the best accuracy.

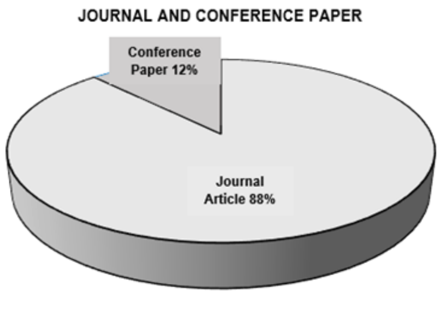

Fig 2. Literature Taxonomy

2.6. Research Methodology

The article focuses on premature birth with the type of algorithm method used. There are three methods used and a total of 67 articles, namely AI (9/67), ML (28/67), and DL (12/67). Result Articles Journal and Conference the number of articles used consisted of two categories, namely journal articles and conference articles namely 67 articles. The final journal article count is 59 (88%). Then, the final number of conference articles is 8 (12%). Below shows the journal articles and conference articles used in this study.

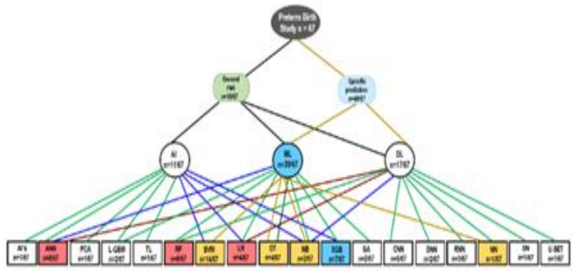

Fig 3. Journal and Conference Articles

2.7. Result by Sources Indexes

The final number of articles used represents 67 articles accessed via full-text reading. The final number of published publications from the IEEE Xplore database is 8 (12%). The number of articles published by Science Direct is 10 (15%) articles. The number of articles selected from Springer was 12 (18%) articles. The total number of articles selected from Scopus is 16, or 24% of the articles. The total number of articles selected from PubMed is 21, or 31%. Figure 2.4 shows the five digital indices used in this study.

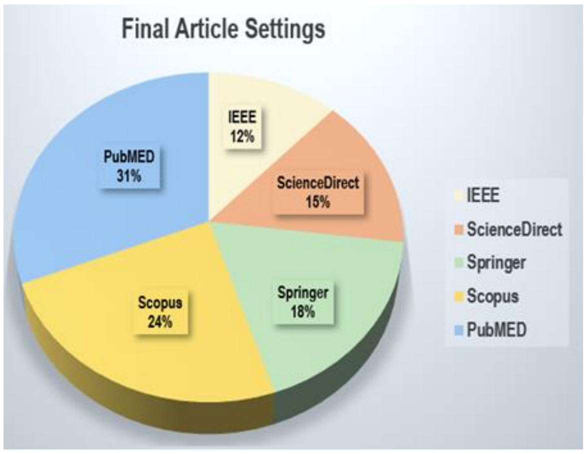

Fig 4. Final Articles Settings

2.8. Result by Categories in Digital Databases

Figure 4 produces five digital database indicators that apply this method in various research articles. The results of the review are divided into five methods used in AI, ML and DL.

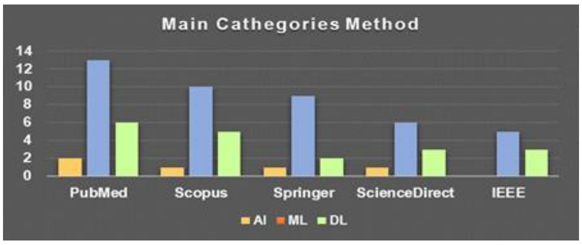

Fig 5. main Categories Method in digital databses

Based on the picture 5 above it can be seen the method used in each article according to the data base.

1. The articles published in the IEEE explore index include 8 articles (5 article using ML and 3 article using DL)
2. The second total of articles published in the Science Direct index is 10 articles (1 article using AI, 6 using ML, and 3 using DL)
3. The third total published in the Springer index is 12 articles (1 article using AI, 9 using ML, and 2 using DL).
4. The fourth total published in the Scopus index is 16 articles (1 article using AI, 10 using ML, and 5 using DL)
5. Then, total published in the PubMed index is 21 articles (2 articles using AI, 13 using ML, and 6 using DL).

2.9 Result of Research Articles by Nationality of Authors

Shows the predicted results of PTB research articles included in this study found from 25 countries.

Fig 6. distribution by authors country

The most widespread studies on PTB are in the USA, China, India, and South Korea. A total of nine studies were conducted in three countries, namely United Kingdom, Australia, and Canada. Two studies were conducted in five countries, Indonesia, Brazil, Finland, Iran, and Spain. Then, finally one study each in the following countries Sweden, Saudi Arabia, Poland, Denmark, Ireland, Japan, Qatar, Sri Lanka, Japan, France, UAE, Italy, Serbia, and Zambia.

2.10. Research Articles by Type of PTB Prediction

The total articles related to the type of PTB prediction were 48 (72%) specific risk, and 19 (28%) common risk articles. The description of each article can be seen in as follows.

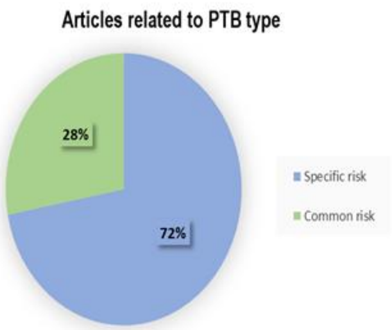

Fig 7. Distribution of PTB Articles by Type Using Prediction

3. Results and Discussion

3.1. Result

3.1.1. Main Features of selected articles

In this research, a feature classification was developed to help identify features that are suitable for use by researchers, in order to achieve optimal algorithm performance. There are several factors that contribute to the increase in the rate of premature birth in pregnancy, which can influence the incidence of premature birth which has an impact on the health of the mother and baby. Therefore, a pregnant woman must undergo regular pregnancy checks, and health workers must be able to detect the health condition of pregnant women during their pregnancy. Feature classification of the 28 selected articles helped reveal the number (percentage) of articles with the following feature categories: pregnancy history (53%), health conditions (17%), investigations (12%), laboratory data (15%), Nutrition (3 %). The sub-features of each feature are shown as follows.

3.1.2. Performance of Machine Learning

Based on findings from selected publications, it can be concluded that machine learning is used to predict preterm birth during pregnancy and delivery. the application of algorithms in research is based on the most accurate modeling. The results of machine learning integration regarding the prediction of premature birth in all selected articles based on Accuracy, AUC, Sensitivity and Specificity. Several researchers have developed a number of algorithm models to determine the most optimal algorithm for predicting the incidence of premature birth. There are 64 articles in this study that focus on the identification or detection of premature birth with algorithm performance results shown in Table 1

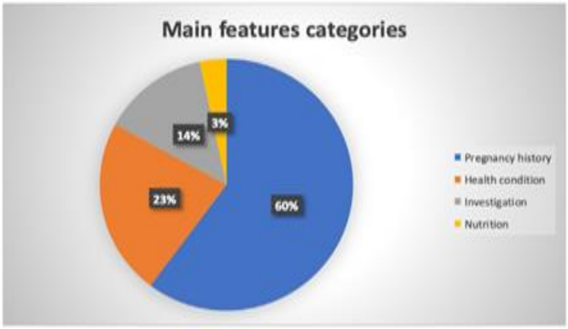

Fig 8. Main Features Categories

Table 1. Performance of Machine Learning Methods.

No	Author & Years	Methods	Results	Object Study
1	Despotovic, D. et al., (2018)[6]	RF, K-NN, SVM	Acc = 0,89 AUC=0, 89 Recall= 0,87	Predicting the preterm delivery from the EHG recordings made between the 22nd and 25th week of gestation, from the publicly available Term-Preterm EHG Database
2	Gao et al. (2019) [26]	BOW & word embedding (NLP), RNN, Regulerised and LR	AUC=0,83 Recall=0,91 Spe=0,70	Prediction of extreme preterm birth from electronic health record
3	Koivu at all (2020)[27]	LR, NN, Gradient Boosting	AUC=0,64	Predicting risk of stillbirth and preterm pregnancies with ML
4	Wlodarczyk et all (2020)[5]	CNN, FCN, Deep-Lab, U-Net	Recall=0,68 Spe = 0,97	Survival prediction of very preterm infants between logistic model & PISA algorithm
5	Leow. et al., (2020)[28]	Validation cohort & Training cohort	AUC=0,86 Sen= 1.0 Spe=74%	Prediction of Preterm Labor, study
6	Ebrahimvandi A. et al., (2022) [29]	RF, GBM, Light GBM	Train AUC=78,34 Test AUC=75,91 Sen=64,82 Spe=73,93 Acc=72,99	Identifying the Early Signs of Preterm Birth from U.S. Birth Records Using Machine Learning Techniques
7	Alsaad R. et al., (2022)[30]	RNNs, GR Boost	ROC-AUC=0,75 PR-AUC=0,40	PREDICTING: AN INTERPRETABLE PRETERM BIRTH PREDICTION
8	Lee J. et al., (2022) [31]	Naïve Bayes, NN, SVM, LR, DT, RF	Acc= 0,90	Predict PTB along with the identification of death risk
9	Zhang Y. et al., (2022) [32]	LR, NNET, ADA, RF, BT, XGB	AUC=0,801, 95% CI= 0,784-0,817	Predicted based on PTB risk analysis and assessment
10	S. Park. et al., (2020) [33]	DT, SVM	Acc=87,0 AUC=0,59 Ratio=0,812 Respectively=77%	Prediction of preterm birth based on machine learning using bacterial risk score in cervicovaginal fluid
11	Degbedzui et all [34]	SVM	ACC=0,97 Recall=0,95 Spe=1,0	Identify accurate diagnosis of term preterm birth by EGC.

12	Nieto del-Amor F.[35]	k-nearest, neighbours, linear discriminant analysis and logistic regression, & ensemble classifier	F1 = 92.04 ± 2.97%	Predict preterm labour using a simple classification with a genetic algorithm
13	Rescinito R. et al (2022).,[36]	RF, SVM	Acc=0,97 Sen=0,84 Spec=0,87	Predict PTB and also detect fetal abnormalities and IUGR based on FHR
14	Rocha Thiago (2021) [37]	Extreme Gr Boosting, LR, DT, RMSE	95% IC= 2.090–2.097	Data-driven risk stratification for preterm birth in Brazil
15	Pollob SM. et al., (2021)[38]	LR, DT	Acc= 87,6 AUC 0,59	PREDICTING RISKS OF LOW BIRTH WEIGHT IN BANGLADESH
16	Santoso N. et all (2018)[39]	Hybrid multivariate adaptive regression splines (MARS) and SVM.	AUC=0,90 Spec= 0,94 Sen=0,86 Acc=93,2	Predicting preterm birth using Hybrid Multivariate Adaptive Regression Splines (MARS)
17	Rawashdeh et all (2020)[40]	Naïve Bayes, DT, K-NN, RF, k NN	Acc=0,95 AUC=0,98 Recall=1,0 Spec=0,94	Intelligence system based on data mining
18	Prema et all P (2019) [41]	SVM, LR	ACC=0,76 Recall=0,84 Spe=0,73 Precision=0,84	Prediction PTB based on maternal chorionic condition by approach ML
19	Esty A. et al., (2018) [42]	DT, NN	AUC=0,81 Recall=0,91 Spe=0,72	Improve the accuracy of the pre-processing method to predict PTB
20	Malacova E. et al., (2020)	Regularised, logistic regression, Decision trees based on classification and regression trees (CART), Random forest, XG Boost, & Multilayer perceptron (MLP) neural network	AUC=66-75% Sen & Spec = -	Validated the predictive accuracy of PTB risk factors and compared ML classifiers
21	Raja R . et al., (2022)[43]	SVM, DT, RL	Acc=0,909 Spec=0,783 Sen=0,89	A MACHINE LEARNING-BASED PREDICTION MODEL FOR PRETERM BIRTH IN RURAL INDIA
22	Chen et all [44]	Wavelet entropy, stacked sparse autoencoder (SSAE)	Acc= 0,90 Recall=0,88 Spec=0,88 Sen=0,92	Detection of preterm birth in electrogastrogram signals based on wavelet transform and stacked sparse autoencoder
23	Seok-Song I. et al., (2023)[45]	RF	Acc=84,03 AUC=84,03-84,04	Assess the association of PTB with dental and gastrointestinal diseases
24	Prema NS et all (2021) [46]	SVM with	Acc=0,87 Pre=0,98 Recall=0,21 Sen=0,98	Machine learning approach for Preterm Birth Prediction Based on Maternal Chronic Conditions

		linear and non-linear kernels and logistic regression, SMOTE	Spec=0,21	
25	Katelyn J. Rittenhouse0 et.al (2019) [47]	Binary Model	AUC=0,877	identify the best set of parameters commonly available at delivery to correctly categorize births as either preterm

Source: Prepared by Author (2023)

It can be seen in Table 1 that the SVM classifier algorithm method is the best method for predicting the incidence of premature birth with an accuracy level of 0.997, recall of 0.995, and specificity of 1.0, for identifying a diagnosis of premature birth which is quite good. Good. accurately. by EGC [34]. These results are similar to the results of Rawashdeh et al.'s research on a data mining-based intelligence system using the Naïve Bayes, Decision tree, K-NN, RF, and NN algorithms with results obtained with an accuracy of 0.95, recall of 1.0, and specificity of 0.94 using RF. The use of small and large samples should be compared to show which method provides the best modelling based on the level of accuracy. In addition, although many algorithm models have been created by previous researchers, many still use retrospective study methodology (table 1). Because the samples used are often pregnant women and women in labour who experienced premature birth. So the use of retrospective study methods is deemed insufficient as a basis for applying machine learning methods in predicting the occurrence of premature births. Therefore, it is important to conduct research using a cohort study method to ensure the research results are more credible. In treating PTB complications, serious clinical management can be used as an effective preventive measure. [24]. Neonatal morbidity which can cause babies to be born prematurely can be avoided by predicting the incidence of PTB early (31). Artificial intelligence and machine learning offer new approaches for predictive modelling, diagnosis, early detection, and monitoring in the perinatal period, which can help practitioners determine the cause of disease and thereby provide the best care for pregnant women [21], [29]. In this case, machine learning can be utilized to help diagnose various diseases and genetic disorders, including PTB [48]. Based on several articles related to preterm birth prediction, several things were found that could be developed in a preterm birth prediction system that needed to be considered, namely as follows; Data collection methods must be consulted with experts such as doctors and other data experts. Data collection needs to be done because the data must be balanced. So influencing the data that will be used in making predictions about premature birth requires balanced data, and the final stage is choosing the right machine learning algorithm for both classification and feature extraction. The learning process must be implemented by dividing it into training, validation, and test sets. In the case of preterm birth, we need to focus primarily on sensitivity and precision, not just accuracy. We must be aware that good results in testing do not guarantee the successful application of the model in real life.

4. Discussion

Preterm birth (PTB) affects 5–18% of pregnancies worldwide[49]. This figure is equivalent to 15 million preterm births each year, and preterm births still account for 75% of neonatal deaths and more than 50% of neurological deficits in children. Premature birth is defined as birth before 37 weeks of gestation, but high mortality and morbidity rates mainly occur in newborns born before 34 weeks of gestation, which is called preterm birth (1-3% of all pregnancies) [50]Early prediction and detection of women at high risk of PTB is critical as it allows timely intervention [5]. high risk of lifelong disability and poor quality of life. PTB complications are the main cause of death in newborns and the second cause of death in children under five. Global efforts to further reduce child mortality require urgent action to address the sources of PTB. Infant mortality and morbidity after PTB can be reduced through interventions in the mother before or during pregnancy and in premature infants after birth (19). Interventions should target all women for primary prevention and reduction of risk of PTB delivery (such as smoking cessation programs) or be used to minimize risk in pregnant women with known risk factors. Health consequences that cannot be avoided in PTB babies at birth include lung immaturity, susceptibility to infection, and neurological complications. Basic and additional care in PTB infants to prevent or treat complications is essential for the disability-free survival of the neonate. PTB is susceptible to severe disease and death in the neonatal period. Without appropriate treatment [34], [51], [52] Some experts define premature birth differently, but most have the same thing as WHO, namely birth that occurs between 20-37 weeks of gestation, or very early premature birth between 20-23 weeks of gestation, early premature birth between 24 weeks of gestation. . -33 weeks, and late preterm birth at 34-36 weeks [52]. Defining the month of preterm birth between 20-37 weeks, very early preterm birth between 20-23 weeks, preterm birth between 24-33 weeks, and late preterm birth between 34-37 weeks 37 weeks. 36 weeks. still, use the term Prematurity and more often define it using low birth weight (LBW) – birth weight less than 2500g, very low birth weight (VLBW) – very less than 1500g, and very low birth weight (ELBW) – birth weight extreme, less than 1000g. [7], [18] According to one expert who is also a specialist in obstetrics and gynaecology, most practitioners who deal with pregnancy problems prioritize treatment over prevention, which of course will result in higher costs. 55 It is not surprising that early detection of PTB is still an unresolved problem. problem. In technological developments, artificial intelligence, in this case, machine learning, can help and play an important role, as well as providing solutions by using various appropriate applications or combining technology[1], can detect and determine the diagnosis of a disease so that it can help the world of health in determining the diagnosis. This comprehensive review of 29 articles helped identify several ML techniques for diagnosing PTB. With artificial intelligence that can be used in all disciplines, all existing algorithms can be further developed to serve specific application domains, such as health and medical services. Trends show that machine learning is gaining ground in the medical field. As underlined, PTB prediction models based on machine learning technology can predict the occurrence of various complications that occur in mothers and babies [53] Therefore, this data can be used by health workers to identify pregnant women who are at high risk of PTB. Considering the high accuracy of various algorithms, especially SG Boost and Random Forest with Boost Tree, it is necessary to carry out further research regarding their use in predicting or detecting PTB in pregnant women, especially in early pregnancies with a gestation period of less than 28 weeks[31], [54]. The findings of this study can be used as an evidentiary basis which can certainly improve midwifery services for pregnant women and postpartum women who undergo PTB screening during their pregnancy [55].

5. Conclusion

Based on the fetus's weight at birth, premature babies can be classified as low birth weight: <2500 grams, very low birth weight: <1500 grams, and very low birth weight: <1000 grams. The most commonly used gestational age-based classification for the degree of prematurity [61] is Early preterm: 32 to <37 weeks, Very preterm: 28 months - <32 weeks, Extreme preterm: <28 weeks. Pathogenesis of Premature Birth The specific cause of PTB is still unclear so PTB is difficult to predict. However, there are several potential causes of PTB, including premature rupture of membranes, lack of prenatal care, defects in the uterus, and health problems for the baby and mother. Other things that contribute to cases of PTB are smoking, use of alcohol and drugs, being overweight or underweight before pregnancy, and a family history of premature birth are also other potential causes of premature birth. To minimize the undesirable consequences of premature birth for the baby and mother, it is necessary to actively monitor the condition of the mother and fetus during pregnancy. Other causes of PTB are seen from several factors, namely: 1) socio-economic determinants including low education, low income, and heavy workload; 2) health-related factors such as body mass index (BMI), diabetes mellitus, hypertensive disorders; and 3) obstetric determinants including infection, parity, vaginal bleeding during pregnancy, history of abortion, caesarean section, placental abruption, placenta previa and/or premature birth [56], [57] Risk Factors for Preterm Birth PTB is influenced by many factors [58,59], follows; absence of a partner, low socioeconomic status, anxiety and stress, depression (life problems such as divorce, separation, death), surgery during pregnancy, problems at work, multiple pregnancies, polyhydramnios, uterine abnormalities, premature rupture of membranes (PROM), history of abortion 2nd trimester, history of cervical surgery, short cervix, sexually transmitted infections (STIs), infectious diseases, bacteriuria, periodontal disease, placenta previa, placental abruption, vaginal bleeding, history of previous premature birth. Pregnancy and childbirth are critical periods that require attention and appropriate action to prevent PTB and reduce maternal and infant mortality rates as well as other detrimental health problems associated with PTB. This intervention includes services provided during pregnancy checks to all pregnant women and women at risk of giving birth to PTB. PTB management services and targeted interventions to improve health behaviour and knowledge about the dangers of PTB and pregnancy complications. This includes the social and economic support needed by disadvantaged families, as well as other interventions that promote universal access to safe maternal conditions and prenatal care. Increasing access to medical services during pregnancy is essential to address the increasing problem of detecting PTB in early pregnancy. Studies show that women who use prenatal care services have a lower risk of premature birth than women who are not covered by the health system [32].Further research needs to be carried out to find out whether there is a relationship between the quality of service provided during pregnancy checks and the differences between mothers who undergo pregnancy checks and those who do not. Prenatal care, and antenatal visits for all pregnant women during the intervention.[34] However, due to limited infrastructure and uneven service facilities, service quality is uneven and service facilities in the regions are lacking. To reduce the incidence of PTB, it is very important that all pregnant women receive ANC services at a minimum according to WHO recommendations, namely minimum ANC services during pregnancy [48]. Integrated pregnancy services are provided to all pregnant women through the provision of health and education services, including stimulation and nutrition, to ensure a healthy pregnancy and the birth of a healthy, intelligent and early fetus. Comprehensive and high-quality detection of pregnancy problems, diseases and complications, preparation for a clean and safe birth, advance planning and preparation for early referral if complications occur, as well as quick and timely recognition. In this field of research, machine learning is well suited to modeling and predicting pregnancy outcomes. So far PTB has not been successfully predicted, treated, or prevented. To identify the most accurate pregnancy diagnosis model, especially for early detection of PTB, more research is needed. Bearing this in mind, future research should focus on developing more robust prediction models using various algorithms, to help predict and detect signs of PTB symptoms in pregnant women early in pregnancy. This can help avoid PTB births by detecting PTB events during pregnancy.

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Conflict of Interest

The Author declares that there is no conflict of interest.

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None.

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