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A hybrid random forest and particle swarm optimization model for early preeclampsia detection

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ABSTRACT

Preeclampsia has become a serious medical problem in the world. Currently, there is no routine or comprehensive screening program in place for preeclampsia, which means that preventive measures are not as effective as they could be, potentially resulting in higher rates of illness and death among mothers and infant. The main purpose of this study is to predict early of preeclampsia using random forest algorithms. This study used a quantitative approach with samples 504. The data were analyzed using random forest with particle swarm optimization (PSO). Random forest have been an accuracy rate of 96.08%, for the area under the curve (AUC), precision, sensitivity, and specificity each (0.971; 97.06%; 97.06%; and 94.12%). Model significantly increased 1.39% after optimize from 94.69% to 96.08%. The design process model algorithm has been validated that have a high level of accuracy based on literature reviews. The quality of services offered will certainly influence people to utilize technology-based services more than conventional ones. Recommendation for field technology and health is building an application model for early prediction of preeclampsia based on machine learning (ML) which is an effort for health workers to provide optimal antenatal care and step in changing technology-based pregnancy checks as initial prevention for pregnant women so that preeclampsia can be avoided.

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1. INTRODUCTION

Preeclampsia is a leading cause of maternal, mortality, and fetal morbidity in the general population [1]-[3]. Preeclampsia is a condition involving high blood pressure that affects multiple organs and occurs in 3% to 8% of pregnancies. When severe, it can lead to complications such as stroke, kidney failure, bleeding in the brain, problems with blood clotting, fluid buildup in the lungs, severe bleeding, and can even be fatal [4]. According to the WHO, preeclampsia occurs seven times more often in developing countries compared to developed ones. Over the past twenty years, the rate of preeclampsia has not significantly declined [5]. This issue is significant not only because preeclampsia affects mothers during pregnancy and childbirth, but also because it can cause long-term complications after birth, such as an increased risk of cardiovascular diseases and other health problems due to damage to blood vessels. As a result, preeclampsia is considered a serious and complex medical issue [6].

In Indonesia, the three main causes of maternal death are bleeding (28%), preeclampsia/eclampsia (24%), and infections (11%). According to the National Guidelines for medical services, the incidence of preeclampsia in Indonesia is 128.273/year or 5.3%. The latest survey data shows Indonesia's maternal mortality rate (MMR) is 305/100,000 live births [7]. The MMR in South Kalimantan tends to fluctuate over the last 3 years. In 2018 the MMR reached 135/100,000 live births. There was a decrease in 2019, which reached 92 cases, and an increase again in 2020 which reached 135 cases. The cause of maternal deaths is primarily due to bleeding and complications of pregnancy and childbirth, namely preeclampsia/eclampsia [8]. Ansari Saleh General Hospital Banjarmasin, which is managed by the local government and serves as a referral center, experiences a high rate of preeclampsia cases. Based on a preliminary study over the past three years, the number of cases has been rising. In 2020, there were 178 cases of preeclampsia (5.92%) out of 3,007 women who gave birth. In 2021, the number was 145 cases (5.17%) out of 2,804 births, and in 2022, it increased again to 168 cases (9.28%) out of 1,813 mothers who delivered [9].

Artificial intelligence (AI) has been applied in various fields because of its ability to solve uncertain problems [10]. Machine learning (ML) is well-suited for predictive modeling of pregnancy outcomes [11]. ML is a branch of AI that uses algorithms and computer models to accomplish specific tasks [12]. It includes approaches such as supervised, semi-supervised, unsupervised, and reinforcement learning. In decision-making scenarios, ML techniques are often preferred over traditional generalized linear models because they typically provide greater predictive accuracy [13]. The optimization algorithm used in this study is particle swarm optimization (PSO). PSO as a possible optimization tool can be a good alternative in optimizing decision tree-based classification rules also an effective algorithm for solving combinatorial problems [14]. PSO is one of the optimization algorithms used in decision-making to determine process parameters that produce the optimum response value [15].

As times and technology develop, the ML algorithms used are growing and getting more sophisticated as they continue. From several research results, the use of ML algorithms in making predictions in cases of preeclampsia also shows a higher level of accuracy [16]. Up to now, early detection of preeclampsia has mainly relied on traditional antenatal care check-ups [17]. Therefore, there is a need for technological solutions that can identify preeclampsia at an even earlier stage. Patients who require action can be identified precisely [18]. According to the research from Sufriyana *et al.* [19] show the random forest model had the best algorithm with an accuracy 0.926 and a sensitivity of 90.7.

According to the problem statement above, management of pregnancy risk problems should now be preventive rather than rehabilitative. Ansari Saleh General Hospital Banjarmasin serves as the first referral for managing pregnancies and childbirth, as well as the lack of implementation of the latest methods in handling this case, particularly by utilizing technology. The early prediction of preeclampsia remains an unresolved issue due to limited access to advanced predictive tools and insufficient integration of data-driven approaches in clinical settings. Therefore, the researcher is interested in conducting research for the early prediction of preeclampsia risk by creating a ML model that incorporates the random forest algorithm and PSO. Accordingly, the results can later be used as an effective way to detect early preeclampsia risk through the development of a pregnancy examination application as a form of prevention, so that pregnant women receive appropriate care from health workers based on technology.

2. RELATED WORK

Preeclampsia is remains a leading cause of mortality among pregnant and perinatal women [20]. Scientists have tried to concentrate on finding a solution to this case, but this has gone beyond the limits of medical treatment to reach a large scale due to the high prevalence among society, so it is necessary to immediately find a solution with the help of technology [21]. Preeclampsia is a multisystem disorder with a complex etiology that specifically occurs during pregnancy. Although the cause of preeclampsia is still unknown, evidence of its clinical manifestations begins to appear from the beginning of pregnancy, in the form of subtle pathophysiological changes that accumulate throughout pregnancy and eventually become clinically apparent [22].

Numerous studies have created algorithms that use ML to predict the occurrence of preeclampsia with accurate predictions that will ensure pregnant women receive appropriate care and are more effective in terms of resource management [23]. One way ML can be used is to build predictive models that identify risk factors for preeclampsia such as, mother characteristic, obstetric, and history of health [24]. ML methods are very effective for supporting research in the health sector and developing ML-based solutions that can be widely applied clinically [25].

Besides developing algorithm models using ML, numerous literature reviews have also explored the application of ML and AI in clinical settings [26]. These reviews offer insights into how such models can predict pregnancy outcomes, serving as a foundation for providing optimal care and treatment [27]. The researchers found random forest performance to be effective in predicting the incidence of preeclampsia [28].

Random forest is an advanced form of the decision tree method that utilizes multiple decision trees. Each tree is trained on different samples, and each attribute is split based on randomly chosen subsets of features [29]. This approach offers several benefits, such as increased accuracy when handling missing data, robustness to outliers, and efficient data storage [30]. Additionally, random forest includes a feature selection process that identifies the most important features, which helps enhance the performance of classification models. By selecting the most relevant features, random forest is able to process extensive and complex data sets effectively [31]. Random forest is an algorithm in ML that is widely used by researchers in building models to predict cases in the health sector, especially pregnancy cases. This is because the random forest has a high level of accuracy in analyzing pregnancy cases [32].

Ranjbar *et al.* [33] discusses cohort studies in assessing the incidence of preeclampsia in early pregnancy in nulliparas using random forest algorithm, and the performance of the British National Institute for Health and Care Excellence evaluated too. Although there are differences in better results compared to NICE, the random forest algorithm produces accuracy that is not superior in predicting preeclampsia in nulliparous women [34]. Base on research Melinte-Popescu *et al.* [6] about model development ML for prediction preeclampsia. The results of this research state that there is an increase in the performance of the ML method compared to conventional models in predicting the development of preeclampsia, where the one of algorithm using random forest with accuracy 0.923. Thus, the use of ML is very effective for pregnancy checks in preeclamptic mothers [6].

The optimization algorithm used in this study is PSO. PSO is a population-based algorithm that has a number of particle. Each hypothetical solution to the problem will be represented by these particles. Each particle changes position with time. In the PSO system, the particles fly around the multi-dimensional search space and adjust their position based on their personal experiences and the experiences of group particles. Several meta-heuristic algorithms can be used as a solution to solve this problem. One of them is the PSO algorithm, PSO can be said to be successful in finding optimal solutions to a problem. PSO has lower complexity, so it can ensure optimal solutions by adjusting global and local searches [14]. Tahir *et al.* [35] has applied PSO to optimize the algorithm so that it can increase the accuracy value. Based on the result research him with the topic risk detection preeclampsia using classification algorithm with PSO. Where in these results an increase in accuracy value of 0.56% was obtained after optimization using PSO. In general, PSO is believed to produce excellent performance in significantly reducing the number of attributes and shortening computing time [35].

3. METHOD

3.1. Collecting data

The initial study started with obtaining approval to gather pregnancy data from the hospital's medical records. The collected data included cases of preeclampsia as the sample group and data from pregnant women without preeclampsia as the control group. The entire population in this study was pregnant women at 2022 in Ansari Saleh General Hospital Banjarmasin which amount to 1,813 births. The samples were categorized into two groups: pregnant women with preeclampsia and pregnant women without preeclampsia. The sampling was conducted using a systematic random sampling method, where the first sample was chosen randomly, and the following samples were selected systematically based on a predefined pattern [36]. The research using a comparing case and control data at a ratio of 1:2, yielded an accuracy of 0.84. using this as a reference, the study included 168 case samples and 336 control samples, totaling 504 samples. Total sampling was applied for the case group, while simple random sampling was used for the control group.

3.2. Algorithm process model

AI-based learning tools were developed to enable solving differential equations [37]. The method in this research based ML using random forest algorithm to predict the incidence of Preeclampsia. The methodology of each research is formed to describe and explain the relationship of the problem, which is the purpose of the research, the methods used, and the tools used to collect and analyze the data. Random forest was chosen because it has several main advantages for predicting health risks such as preeclampsia, as it can handle high-dimensional and varied data and has good tolerance to overfitting. PSO was selected for optimizing the hyperparameters of the random forest model efficiently. Therefore, the combination of random forest with PSO provides a strong approach for preeclampsia prediction with a model that is not only accurate but also easy to optimize and understand. To measure the model's performance more accurately, 10-fold cross-validation is used so that the analysis results can be more reliable.

In this research, the process model is divided into 3 steps, namely the first step of collecting data and then split data. The next step is to build a model, and the last step is optimization algorithm. Explained about process model algorithm can be seen on the Figure 1.

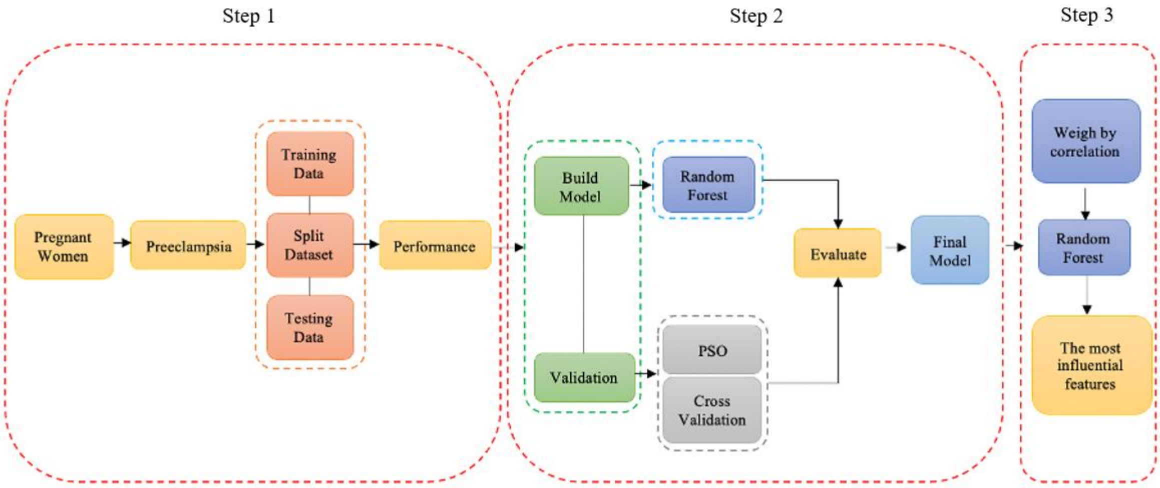


Figure 1. Process model algorithm

The first stages is a design algorithm of data processing, in this research were carried out by split the data training and testing. Split data using trying a ratio of 90/10, 80/20, 70/30, and 60/40 for to choose the best algorithm [38], and then build model of the ML algorithm using random forest. The second step is optimization algorithm by PSO and validate model using cross validation to show the final model. The last step is to determine the most important features using the weight by correlation method.

3.3. Features

This study used quantitative approach with observational approach for the data collection. Observation is an accurate and specific method for collecting data and seeking information about all activities that are the object of the research study. Table 1 is a parameter used for early prediction of preeclampsia divide into 3 (three) categoric such as profile, obstetric, and health.

Table 1. Parameters used for early prediction of preeclampsia

Categoric	Features
Profile	Age, education, and profession
Obstetric	Gravidity, parity, antenatal care, pregnancy interval, history of abortion, history of caesarean section, and history of preeclampsia
Health	Hypertension, diabetes mellitus, hemoglobin, and body mass index

4. RESULT AND DISCUSSION

4.1. Result

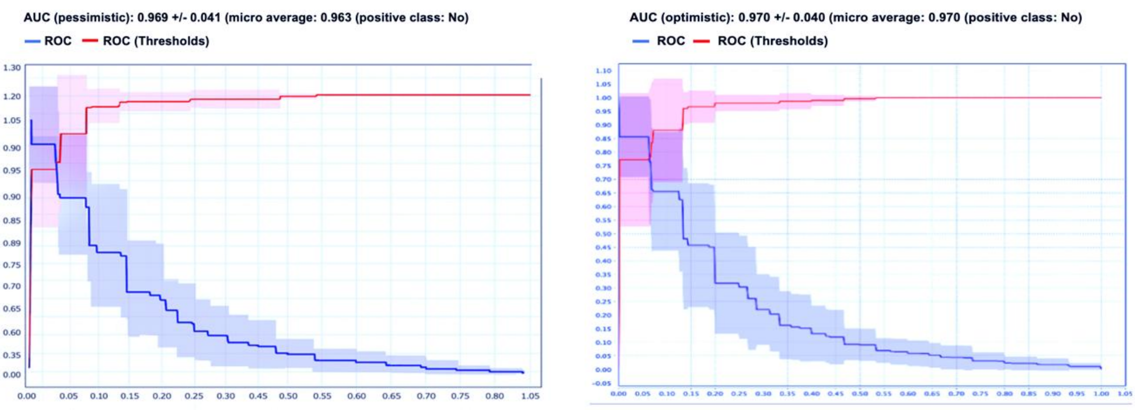
The results of this study are in accordance with the objectives of the research made. Build model for early prediction preeclampsia based method ML using random forest algorithm carried out through several step. The first step of algorithm testing is to split the data. The ratio of dividing training data and testing data uses a ratio of 90/10, 80/20, 70/30, and 60/40. The accuracy results for each ratio and all algorithms can be seen in the Table 2.

Table 2. Split data

Algorithm	Ratio			
	90:10	80:20	70:30	60:40
Accuracy	94.69%	94.55%	94.06%	92.75%
AUC	0.969	0.969	0.965	0.949
Precision	95.48%	95.44%	94.70%	93.88%
Sensitivity	96.67%	96.67%	96.58%	95.55%
Specificity	90.73%	90.30%	88.98%	87.13%

Based on the Table 2 the data were split with a ratio of 90% for training and 10% for testing, resulting in a ML model that achieved excellent predictive performance. An accuracy of 94.69% indicates that the majority of the model's predictions correspond well with the true outcomes. The area under the curve (AUC) value of 0.969 demonstrates the model's strong ability to discriminate between preeclampsia and non-preeclampsia cases. A precision of 95.48% signifies that most positive predictions made by the model are true positives (actual preeclampsia cases). sensitivity of 96.67% reflects the model's high effectiveness in correctly identifying nearly all true preeclampsia cases, while a specificity of 90.73% indicates a good capability to recognize non-preeclampsia cases accurately. Collectively, these metrics describe a highly effective and reliable predictive model suitable for clinical application. The AUC graphic from split data can see on the Figure 2.

The Figure 2 displays two AUC curves, each representing the AUC value for two different models or prediction scenarios. The curve illustrates the model's ability to distinguish between positive and negative cases, with Figure 2(a) showing an AUC of 0.969, indicating an excellent, nearly perfect classification performance, high sensitivity, and a low false positive rate. Meanwhile, the Figure 2(b) shows an AUC of 0.970, which is also very good, although slightly lower than the left. The colored areas on the graphs represent the confidence and variation of predictions at the tested thresholds. An AUC value above 0.9 reflects excellent model performance and makes it highly suitable for clinical applications and decision-making requiring high accuracy. After getting the best ratio, the second step is optimization algorithm by PSO and cross validation to show the increase accuracy get the last performance as evaluation model can be seen on Table 3.



(a) (b)

Figure 2. AUC ratio; (a) AUC pessimistic and (b) AUC optimistic

Table 3. Performance model

Model	Acc (split data 90/10)	Acc (PSO)	Percentage	I/D
Random forest	94.69%	96.08%	1.39	Increase

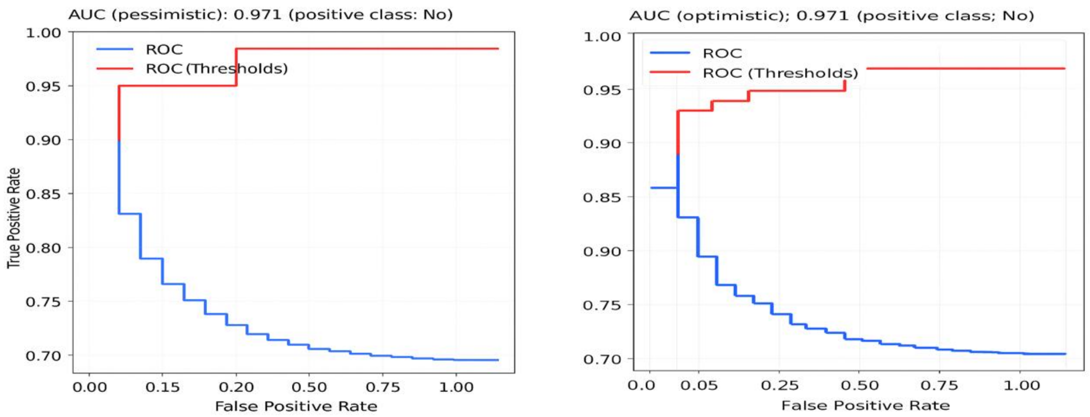
After optimization and validation, there is an increase in accuracy for random forest algorithm as much 1.39%. The next step is evaluation model to see the effectiveness random algorithm for early prediction preeclampsia can be seen on Table 4.

Table 4. Evaluate model

Model	Acc	AUC	Prec	Sens	Spec
Random forest	96.08	0.971	97.06	97.06	94.12

From the results of the final model evaluation obtained in this research, level accuracy random forest algorithm 96.08%, Statistically, the AUC value of 0.971 is evaluated as having a level of accuracy very high, for precision which is the ratio of true positive predictions compared to the overall positive predicted results 97.06%. Sensitivity is many percentages of pregnant women are predicted to experience preeclampsia compared to all pregnant women who experience preeclampsia, on this research is a 97.06%. For the specificity it is the correctness of negative predictions compared to the overall negative data or how percentage of pregnant women were correctly predicted not to have preeclampsia compared to the total number of pregnant women who were correctly predicted not to have preeclampsia is 94.12%. The last model of AUC can be seen on the Figure 3.

Based on Figure 3, the pessimistic (Figure 3(a)) and optimistic (Figure 3(b)) AUC values are identical, both measuring 0.971, indicating consistent and robust performance of the model across different evaluation perspectives. The final step involves identifying important features, which are indices in the dataset that represent the relative significance of each feature in predicting the target variable, in this case, preeclampsia. To assess the accuracy of these important features, a correlation-based weighting model is used. This approach quantifies how strongly each feature is related to the outcome, helping to highlight the most influential predictors in the model. Table 5 are the weight results from largest to smallest.



(a) (b)

Figure 3. AUC after pessimistic and validation; (a) AUC pessimistic and (b) AUC optimistic

Table 5. Features of important

No	Categoric	Features	Weight
1	Obstetric	History of preeclampsia	66.83
2	Obstetric	History of caesarean	63.80
3	Health	History of hypertension	55.83
4	Health	History of diabetes	41.12
5	Profile	Mother age	22.19
6	Obstetric	Pregnancy interval	18.92
7	Profile	Education	14.52
8	Obstetric	Parity	11.07
9	Health	Hemoglobin	10.61
10	Obstetric	Gravidity	7.50
11	Health	BMI	5.03
12	Profile	Profession	4.51
13	Obstetric	Antenatal care	1.80
14	Obstetric	History of abortion	0.00

Of the 14 (fourteen) features, there are 9 features that have a weight correlation above 10%. We can see the most significant factor contributing to preeclampsia is a prior history of the condition (66.83%), history of caesarean section (63.80%), history of hypertension (55.83%), and history of diabetes mellitus (41.12%).

4.2. Discussion

The study's results highlight the successful development of a ML model using the random forest algorithm for early prediction of preeclampsia. The model demonstrated excellent accuracy and strong classification metrics, including high sensitivity, specificity, precision, and AUC values above 0.97, underscoring its robust predictive capability. The enhancement of model performance through PSO and cross-validation confirms the importance of careful hyperparameter tuning and rigorous evaluation to optimize predictive accuracy. This optimization process resulted in a meaningful gain in accuracy, which can translate to improved clinical decision-making, timely intervention, and better maternal-fetal health outcomes. The identification of key features such as history of preeclampsia, caesarean section, hypertension, and diabetes mellitus corroborates known clinical risk factors, emphasizing the model's clinical relevance and interpretability. These insights can help healthcare providers focus on high-risk individuals for closer monitoring. From the results of the final model evaluation obtained in this research, level accuracy random forest algorithm 96.08%.

The most significant factor contributing to preeclampsia is a prior history of the preeclampsia, history of caesarean section, history of hypertension, and history of diabetes mellitus. A previous history of preeclampsia is a strong risk factor for recurrence in subsequent pregnancies because it reflects underlying maternal vascular and placental abnormalities that tend to persist or recur. Women who have experienced preeclampsia before are reported to have a significantly higher risk—up to 6.9 times greater—of developing the condition again, due to predispositions in endothelial dysfunction, abnormal placentation, and immune maladaptation [39]. This recurrent risk is supported by multiple studies indicating that preeclampsia tends to cluster in certain individuals, often compounded by genetic and familial factors. The pathophysiological basis involves chronic inflammation, oxidative stress, and impaired placental blood flow, which collectively contribute to disease reappearance in future pregnancies. A history of cesarean section is associated with an increased risk of preeclampsia due to several reasons. First, women who had previous cesarean deliveries may have underlying uterine or placental abnormalities, such as scar tissue or impaired placental implantation, which can disrupt normal blood flow and contribute to the development of preeclampsia. Additionally, cesarean section is often performed in complicated pregnancies, which may share common risk factors with preeclampsia, including hypertension and impaired placental function. Studies have found a statistically significant correlation between a history of cesarean delivery and the occurrence of preeclampsia, with odds ratios suggesting a meaningful increase in likelihood compared to women without prior cesarean births [40]. A history of hypertension is a well-established risk factor for preeclampsia because chronic hypertension contributes to endothelial dysfunction, impaired placental perfusion, and increased systemic inflammation, which are key mechanisms in the development of preeclampsia. Women with pre-existing hypertension have a significantly higher likelihood of developing preeclampsia, as their vascular system is already compromised before pregnancy. This can lead to abnormal placental blood flow, oxidative stress, and heightened inflammatory responses during pregnancy, increasing the risk of complications such as preeclampsia, HELLP syndrome, and eclampsia [41]. A history of diabetes mellitus increases the risk of developing preeclampsia because diabetes causes vascular endothelial dysfunction, oxidative stress, and impaired placental development. Insulin resistance associated with diabetes contributes to inflammation and vascular injury, which are key in the pathogenesis of preeclampsia. Pregnant women with diabetes have a significantly higher likelihood of developing preeclampsia compared to those without diabetes, with studies reporting odds ratios ranging from approximately 3.6 to 5.8 times greater risk. This heightened risk is due to the combined effects of metabolic disturbances and endothelial damage intrinsic to diabetes, which exacerbate placental ischemia and systemic hypertension during pregnancy [42], [43].

5. CONCLUSION

Preeclampsia is one of the most dangerous causes of complications in pregnancy and the leading cause of death which is still a serious problem that needs to be handled optimally. ML has the potential to be employed to predict preeclampsia and can differentiate patients who will experience preeclampsia in the first trimester of pregnancy. The findings of this study demonstrate that the ML model based on the random forest algorithm can effectively predict the risk of preeclampsia early on, achieving high accuracy, sensitivity, specificity, precision, and AUC values, all exceeding 90%. This highlights the model's strong discriminative power between preeclampsia and non-preeclampsia cases, making it a reliable tool for clinical decision-making. The optimization with PSO further improved the model's accuracy, reinforcing the potential of advanced AI techniques in maternal health risk prediction. These results have important implications for both the research field and clinical community. For researchers, the study validates the application of ML algorithms, especially random forest combined with optimization methods, in tackling complex clinical prediction problems such as preeclampsia. It encourages further exploration of AI-based risk assessment tools that leverage multifactorial clinical data. For the clinical community, this model offers a promising approach to facilitate early detection and timely intervention, which can reduce maternal and fetal complications related to preeclampsia. A fast system based on precise personal preferences can be the right health recommendation. However, the study is limited by its single-site data collection, which may affect the generalizability of the model across diverse populations and settings. Future work should aim to validate and refine the model using multi-center, larger, and more heterogeneous datasets to enhance external validity.

Additionally, exploring integration of biochemical markers or genomic data might further improve prediction performance.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors affirm that they have no financial, personal, or professional conflicts of interest that might have impacted the results or interpretations of this study. All research activities, analyses, and conclusions were performed objectively and independently. Any possible affiliations or funding sources have been fully disclosed, and none have compromised the integrity of this work.

ETHICAL APPROVAL

This research has obtained approval from the Government of Banjarmasin City Badan Kesatuan Bangsa dan Politik, Government of Banjarmasin City with the number 072/909/sekr/Bakesbangpol.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article. The data that support the findings of this study are available from the corresponding author, [initials: TAR], upon reasonable request.

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