Predicting Fetal Condition from Cardiotocography Results Using the Random Forest Method

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Abstract. Cardiotocography is an important process in pregnancy as fetal monitoring. It monitors the baby's heart rate in a healthy condition or not. Apart from that, this can also measure whether the movements carried out by the baby in the womb are normal or not. This study extracted the recording data by cardiotocographs. The attributes of fetal data that have been recorded amount to 22. They were used as the indicators in determining the conditions of the fetus whether under normal circumstances, suspect or pathologic. The prediction of the fetus condition was based on the Random Forest method. Also, the method was compared with the Naïve Bayes and Decision Tree methods. The accuracy of the Random Forest method reached 95.11%. It was higher compared to using other methods.

Keywords: Cardiotocography, Radom Forest, Naive Bayes, Decision Tree

1 Introduction

Pregnant women certainly hope to have a healthy pregnancy, so the baby is born into the world safely. However, there are several conditions that make a baby die in the womb (stillbirth) [1]. The baby dies in the womb or stillbirth is a condition in which the baby dies in the womb after the pregnancy is over 28 weeks. In some cases, there are also babies who die during labor, but the percentage is small. No one knows the exact cause of a baby dying in the womb. However, there are several factors that are likely to increase the risk of stillbirth, including placental disorders, diseases suffered by pregnant women, infections, birth defects, and babies wrapped around the umbilical cord [2]. It can be prevented if a mother knows the condition of herself and her child during pregnancy so that during the process of labor or earlier actions can be taken in accordance with the condition of the mother and child [3]. One effort that can be done through routine check-ups to the obstetrician [4].

There are so many types of checks during pregnancy. One of them is a cardiotocography examination. Cardiotocography (CTG) is a technical way to record fetal heart rate and uterine contractions during pregnancy [5]. It records changes in fetal heart rate and temporal relationship with uterine contractions. It is one way to reduce MMR because it aims to identify the state of the fetus and determine whether the baby needs to be born by cesarean section or normal. The state of the fetus is seen in terms of oxygen levels and the baby's heart rate [6]. It can also be used during labor so that it can monitor the condition of the mother and child. In general, it is done on the recommendation of an obstetrician. However, patients can request the examination because it is so important.

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Its results can assess whether the condition of the fetus and the mother is in good condition or not, which is expected to reduce fetal death and save lives [7]. So now the various its results are collected for research on the condition of the fetus. The data is used to see indicators of the condition of the fetus from various aspects that can be seen in the process. Its indicator will be used to predict the condition of the fetus so that the mother and baby will be careful and get information for the safety of both.

The future of the world of health cannot be separated from digital technology. Rapid technological advances have also had an impact on the health sector [8]. Technological developments play a role in helping doctors and health practitioners build better quality health care. Artificial intelligence (AI) has become one of the technologies that play an important role in redesigning existing health care [9]. The algorithm makes it easy for patients to get services and medical assistance quickly and precisely. Likewise, for medical personnel, AI has a role in accelerating patient management, helping to analyze diseases, and even prescribing medicines that are appropriate for patients.

In terms of technological progress, it can also contribute in the form of spotting the process of analysis from CTG. Indicators of the state of the fetus can be considered good or cannot be produced from the process of data processing with the classification process. The classification can be done by various methods. One of them is through machine learning [10]. In the world of health, the method has been successful in various fields including sleep stage classification [11-12], protein clustering [13], and classification of tissue engineering pathology [14].

This study applies a random forest for classification. Random forest is one of the methods in the decision tree [15]. A decision tree is a flow diagram that is shaped like a tree that has a root node that is used to collect data. An inner node located at the root node that contains questions about data and a leaf node that is used to solve problems and make decisions [16]. The decision tree classifies a sample of data that is not yet known class into existing classes. Use a decision tree to avoid overfitting a data set when it reaches maximum accuracy. It is the reason for this algorithm used in this study.

2 Principles of Random Forest Algorithm

Random forest is one of the machine learning methods which is a method based on the formation of a decision tree. The method combines the classification and regression tree methods so that they are able to overcome non-linear problems [17]. It is a combination of each good tree and then combined into one model. Random forest relies on a random vector value with the same distribution on all trees where each decision tree has maximum depth.

A random forest is a classifier consisting of a tree-shaped base classifier, as shown by **Figure 1.** The tree is a combination of other tree units. Each tree in a unit will choose the most dominant class in the x input. The characteristics of the random forest are:

1. It avoids overfitting
   It is formed from other trees. Trees are built from weak classifiers. Although there are many trees in the random forest, this method avoids overfit. This is because the error function is to control the addition of trees.
2. Feature selection via bagging
   Bagging is used for random feature selection. Each training set is taken with a replacement from the original training set. Then a tree is planted in a training set

using random feature selection. There are two reasons for using bagging. First is increased accuracy when the random feature is used. The second is to provide an estimate of the generalization error of the combined tree and estimate the strength and correlation. The simplest random forest with random features is formed by random selection, at each node, a small group of divided input variables. Form a tree using the CART methodology to the maximum size.

3. The combination function is linear
   This method defines more features by taking random linear combinations from a number of input variables. The feature is variable L, which is the number of variables combined. The variable L is randomly selected and added together with a coefficient that has a random number [-1,1].

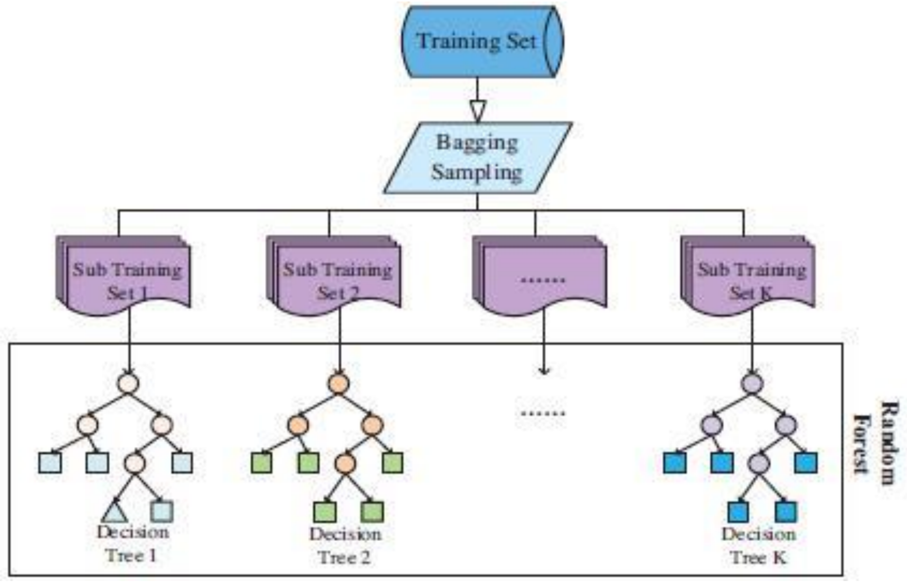

Fig. 1. Construction of a random forest.

The steps in forming a random forest are:

a. Select a training set for each tree
   The bagging sampling technique is mainly used in the random forest algorithm to generate K training subsets with certain repetitions from the original training set through random and then put back sampling methods [18].
b. Build each decision tree
   After the training subsets are obtained, the feature subspaces (the number of features is usually $\lfloor \quad _2 + 1\rfloor$, M is the total number of features) are selected from each training subset to generate the K decision trees, thereby forming a “random forest”. The main idea is to build many classification decision trees to vote for a given sample to provide a class label, while each tree is built based on binary splits and trained through a bootstrap sample set, which means only about two-third of training data is used and remaining one-third data is called out-of-bag (OOB) [19]. Trees are built until they reach the maximum size (without pruning) and apply random feature selection to each selection process. So that not all features are used in every division of the tree node.

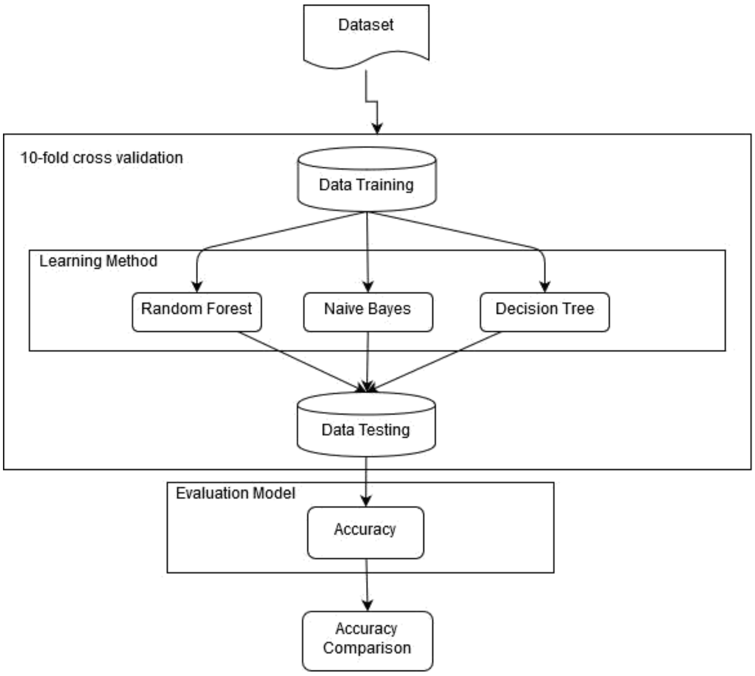

Fig. 2. Research methodology.

3 Research methodology

The research methodology is shown in **Figure 2.** The data from this study comprises Fetal Heart Rate (FHR) and Uterine Contraction (UC) classified by expert doctors [20]. There are 2126 CTG results. The dataset consists of 1655 normal state data, 295 suspicious state data, and 176 pathologic state data. The summary of CTG features is shown in Table 1. Each feature is described through its statistical data in the form of the maximum value (max), minimum value (min), mean value (mean), and standard deviation value (stdev). All features are numeric. The study compared random forest with several other methods, namely naive Bayes, and decision trees. Naive Bayes is a machine learning method that uses conditional probability calculations on the Bayes theorem. This algorithm makes use of probability and statistical methods. The method predicts future probabilities based on past experience [21]. The decision tree is a classification algorithm that is often used and has a structure that is simple and easy to interpret [22].

In this study, the maximum iteration of Bagging in a random forest was 100 with a batch size of 100. The base classifier was a random tree. The tree from the random tree was then used to form a random forest. Similar to the random forest, the other two methods also had the same batch size. The confidence factor of the decision tree was 0.25. The pruning process was also applied to the decision tree that was built.

After the model of each method was obtained, the next step was an evaluation by comparing the accuracy and RMSE among the three methods. The evaluation mechanism was based on 10 fold cross-validation. The confusion matrix was also an evaluation parameter to analyze the performance of these three methods.

Table 1. Summary of dataset features.

No.	Features	Max	Min	Mean	Stdev
1	Tendency	1	-1	0.32	0.61
2	Acelerations (@second)	0.02	0	0	0
3	Light decelerations (@second)	0.02	0	0	0
4	Severe decelerations (@second)	0	0	0	0
5	Prolonged decelerations (@second)	0.01	0	0	0
6	Fetal movements (@second)	0.48	0	0.01	0.05
7	Uterine contractions (@second)	0.01	0	0	0
8	Abnormal short-term variability (%)	87	12	46.99	17.19
9	Abnormal long-term variability (%)	91	0	9.85	18.4
10	Mean value of short-term variability	7	0.2	1.33	0.88
11	Mean value of long-term variability	50.7	0	8.19	5.63
12	Histogram mode	187	60	137.45	16.38
13	Histogram mean	182	73	134.61	15.59
14	Histogram median	186	77	138.09	14.47
15	Histogram variance	269	0	18.81	28.98
16	Histogram peaks	18	0	4.07	2.95
17	Histogram zeros	10	0	0.32	0.71
18	FHR baseline (@minute)	160	106	133.3	9.84
19	Width of FHR histogram	180	3	70.45	38.96
20	Minimum of FHR histogram	159	50	93.58	29.56
21	Maximum of FHR histogram	238	122	164.03	17.94

4 Results and Discussion

The performance of the three methods is shown in Table 2. Based on accuracy and RMSE, the random forest had the best performance compared to the other two methods. The decision trees also obtained accuracy above 90%. It showed that the tree method had good performance for this data compared to naive Bayes. But bagging on random forests had proven to be effective in improving performance on the tree method. It caused the random forest to be superior to the decision tree. On the other hand, naive Bayes only had an accuracy of 82.27%. The Bayes' theorem proved to be less effective in this study.

The analysis of the results based on the confusion matrix is shown in Tables 3, 4, and 5. These three tables describe the prediction results of the models that had been built from each method. These three methods had unique advantages in predicting each class. The normal class was best predicted by random forest. The suspect class was the best predicted using naive Bayes. Unlike the case with the decision tree, the method was most successful in predicting pathologic class.

Table 2. Comparison of Accuracy and RMSE of each method.

Method	Accuracy	RMSE
Random forest	95.11 %	0.16
Naive bayes	82.27 %	0.33
Decision tree	92.71 %	0.21

Table 3. Confusion matrix of random forest.

	Classified as		
	Normal	Suspect	Pathologic
Normal	1631	21	3
Suspect	55	233	7
Pathologic	10	8	158

Table 4. Confusion matrix of naive Bayes.

	Classified as		
	Normal	Suspect	Pathologic
Normal	1391	201	63
Suspect	31	248	16
Pathologic	4	62	110

Table 5. Confusion matrix of decision tree.

	Classified as		
	Normal	Suspect	Pathologic
Normal	1585	57	13
Suspect	66	225	4
Pathologic	9	6	161

5 Conclusion

This study compared random forest, naive, and decision trees in classifying fetal conditions based on cardiotocography. The evaluation based on 10 fold cross-validation. The performance was measured using accuracy and RMSE. But, it could be seen that the accuracy of the random forest and decision tree methods was not much different. Because random forest also had a decision tree concept where random forest would make a lot of trees so it is called a forest. Table 2 shows the random forest had the highest performance compared to the two other methods. The method had high accuracy but low RMSE. If analyzed based on the confusion matrix as shown in Tables 3, 4, and 5, each method had advantages in predicting a class. The normal class was best predicted by random forest. The suspect class was best predicted using naive Bayes. Unlike the case with the decision tree, this method was most successful in predicting pathologic class. With the high accuracy of the three methods, the modeling that had been done can be used to predict the fetus. So it is expected to be useful by providing information to women who are pregnant related to the condition of the fetus.

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