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Short birth intervals classification for Indonesia's women

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ABSTRACT

Birth interval is closely related to maternal and infant health. According to world health organization (WHO), the birth interval between two births is at least 33 months. This study is the first to discuss the short birth interval (SBI) in Indonesia and used data from the Indonesian Demographic and Health Surveys 2017 with a total of 34,200 respondents. Birth interval means the length of time between the birth of the first child and the second child. Categorized as SBI if the distance between births is less than 33 months. The variables used include mother's age, mother's age at first giving birth, father's age, household wealth, succeeding birth interval, breastfeeding status, child sex, residence, mother's education, health insurance, mother's working status, contraception used, child alive, total children, number of living children, and household members. Machine learning algorithms including logistic regression, Naïve Bayes, lazy locally weighted learning (LWL), and sequential minimal optimization (SMO) are applied to classify SBI. Based on the values of accuracy, precision, recall, F-score, matthews correlation coefficient (MCC), receiver operator characteristic (ROC) area, precision-recall curve (PRC) area, the Naïve Bayes is the best algorithm with scores obtained 0.891, 0.889, 0.891, 0.885, 0.687, 0.972, and 0.960 respectively. Additionally, 18.25% of mothers were classified as still giving birth within a short interval.

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1. INTRODUCTION

Birth interval is closely related to maternal and infant health [1]–[3]. Maternal and infant health is one of the important points in the sustainable development goals (SDGs), especially for good health and well-being [4], [5]. Although there is no clear research that short birth interval (SBI) can cause maternal and infant mortality deaths directly, the impact caused by short birth interval is likely to be detrimental. It can cause premature birth, especially for newborns [6], [7]. In addition, the short birth interval can also result in non-optimal nutrition for newborns, including receiving exclusive breastfeeding. Further impact, stunting, or wasting can occur. According to world health organization (WHO), the recommendation of a birth interval is 33 months after the previous birth [8]–[10]. The right distance between births can help the mother recover, both physically and psychologically to deal with the next birth. So, the right birth distance can maintain maternal, perinatal, neonatal, and child health.

Indonesia, as a developing country still experiencing problems in the field of health, specifically the health of mothers and children. In the Southeast Asian region, Indonesia occupies the highest position in maternal mortality [11], [12]. By 2010, the maternal mortality rate (MMR) value was recorded at 346 per 100,000 live births. While related to the infant mortality rate (IMR), the value was 32 per 1,000 live births in

2012. Hence, the improvement of maternal and child health needs to be done. Therefore, studying the distance between births is the objective of this research. The other purpose of this study is to be able to find out a clear picture of birth spacing in Indonesia and want to know the factors that affect birth spacing.

There have not been many studies on the birth interval in Indonesia. Short birth interval significantly affects neonatal mortality in Indonesia [13]. This study used 15,952 singleton live-born infants born from 1997 to 2002 and implemented multilevel logistic regression (OR=2.82, p=0.00) as its method. Another study about birth interval found that area of residence, education of mother, and age of mother influence to a birth interval in West Papua and Yogyakarta, Indonesia [14]. The birth interval in this research means the interval between marriage and the time when the first child is born. Cox extended was used and the hazard ratios are 0.720, 1.708, 2.648, 4.361, and 0.955 for the area of residence, education of mother (finished primary school, junior high school, senior high school), and age of mother respectively. The other study about short birth intervals is conducted using secondary data from Indonesia Demographic and Health Surveys 2012 and found that shorth birth interval is one of the factors that cause maternal and infant mortality [15]. It studied birth spacing among multiparous women in Indonesia with Mann Whitney, Kruskal Wallis, and logistic regression as a methodology. The result concluded that 22.8% of women gave birth within less than 3 years of previous birth. A study on birth spacing and its relationship to infant mortality has been carried out and found that the two are negatively related [16]. This study implemented survival analysis, Cox proportional hazard, as its method. It concluded that babies born less than 36 months from the previous birth were more likely to die than babies born with a birth span of more than 36 months.

From previous research, we have a result that short birth intervals still happen in Indonesia year by year and it can harm maternal and infant health. This study is conducted to determine the classification of short birth intervals in Indonesia. We design a new technique to classify them, i.e. machine learning algorithms to know the composition between normal and short birth intervals. We use data from the Indonesia Demographic and Health Survey 2017. On top of that, this study wants to know the prevalence of mother and child adverse health in Indonesia through the birth interval.

2. METHOD

This study used secondary data, namely the Indonesian Demographic and Health Surveys 2017. Data was collected and maintained by the National Population and Family Planning Board, Statistics Indonesia, Ministry of Health, in collaboration with intermunicipal collaboration framework (ICF) under the Demographic and Health Surveys (DHS) program [17]. Survey data is an annual program, which previously was held in 1987, 1991, 1994, 1997, 2002-2003, 2007, and 2012. The samples were women of childbearing age 15–49 years old in 34 provinces in Indonesia.

The sample of respondents included 34,200 women. Nevertheless, the number of samples included in the SBI category was 8,286 (24.23%). Categorized as SBI if the birth interval is less than 33 months [10]. And the rest, women presumed as normal in the birth interval. Several variables used include mother's age, mother's age at first giving birth, father's age, household wealth, succeeding birth interval, breastfeeding status, child sex, residence, mother's education, mother's working status, contraception used, child alive, total children, number of living children, household members, and health insurance [18]–[22].

We started by preprocessing the raw data. In the first step, we select variables that correspond to the interval of childbirth. Then, check for the completeness of data. In the next step, we normalize the continuous attribute. Afterward, encode the short birth interval attribute into 1 and 0. Categorize as an SBI if birth interval greater than 0 months but less than 33 months, otherwise categorize as not SBI. Then, split data using 10-fold cross-validation.

In this study, we implemented various algorithms for classification. Logistic regression, Naïve Bayes, sequential minimal optimization (SMO), and lazy locally weighted learning (LWL) were used to classify SBI [23]–[26]. Logistic regression is a classic statistical method, as well as a common algorithm in classifying binary class, yet it has drawbacks when applied to build in complex multivariable nonlinear relationships [24], [27]–[29]. Naïve Bayes is an algorithm that remains the most effective and efficient in classification tasks. This algorithm offers simplicity and less computational runtime [24], [25], [28]. SMO is an effective method for training the support vector machines (SVMs), especially on the sparse dataset. This method was chosen because, in Indonesian Demographic and Health Surveys 2017 dataset, the target variable is mostly equal to the zero values. Then, LWL has the advantage that it is extremely adaptable and provides a precise model in the long run [30]. The selection of the best model is done by looking at several criteria for the goodness of the model, namely: matthews correlation coefficient (MCC), area under the receiver operator characteristic (ROC) curve area under the curve (AUC), precision-recall curve (PRC) area, accuracy, precision, recall, F1-score [31]–[33].

3. RESULTS AND DISCUSSION

Preprocessing omitted 2 observations because of incomplete information. So that the total observation was 34,198 women. By this number, 75.77% of mothers were classified as not short birth interval or they gave a normal interval of birth, and the rest 24.23% were categorized as a short birth interval. A short birth interval means that the interval between birth is less than 33 months.

Table 1 illustrates some of the main characteristics of the respondents sociodemographic. More than 50% of mothers as respondents were secondary education level (51.89%), followed by primary (32.44%) with the highest birth interval which on average is 47.02 months. Mothers with higher education levels (13.48%) have the lowest average birth interval i.e. 30.97 months. This result is similar to the study by [14], [15] and equal to the report by [2] which stated that women in higher education levels have a higher risk of giving short birth intervals than lower education levels. Many factors affect this condition, such as age and female fertility. Women who graduate from higher education tend to graduate at an older age than women who are not highly educated. In addition, related to fertility, the older a woman is, the less her fertility is. Therefore, it is not surprising that women with higher education tend to give birth with a shorter duration.

Of the total respondents, more than half of them live in urban areas (50.47%) with an average birth interval of 40.94 months. This interval is slightly longer than the average birth interval for women living in rural areas. This output is consistent with research that stated that women who gave birth in cities tend to have longer intervals [13], [14].

Table 1. Distribution of respondents' sociodemographic characteristics based on the average birth interval

	n (%) $N = 34{,}198$	Average of birth interval (in months)
Mother's education		
No education	752 (2.20)	37.70
Primary	11,093 (32.44)	47.02
Secondary	17,744 (51.89)	39.72
Higher	4,609 (13.48)	30.97
Residence		
Rural	16,939 (49.53)	40.79
Urban	17,259 (50.47)	40.94
Household wealth		
Poorest	8,062 (23.57)	36.21
Poorer	6,672 (19.51)	41.43
Middle	6,568 (19.21)	42.87
Richer	6,559 (19.18)	43.09
Richest	6,337 (18.53)	41.82
Contraception used		
No method	13,248 (38.74)	33.13
Traditional method	2,367 (6.92)	39.64
Modern method	18,583 (54.34)	46.54
Mother's working status		
No	14,219 (41.58)	39.96
Yes	19,979 (58.42)	41.51
Child alive		
No	2,138 (6.25)	30.38
Yes	32,060 (93.75)	41.56

Based on the household wealth variable, more respondents are in the poorest category (23.57%) while other wealth categories tend to be balanced with a percentage of 18–19%. The condition of the mother with the poorest economic level also resulted in the short distance between births, i.e. 36.21 months. Meanwhile, for the other economic level categories, the birth intervals are similar which is between 41-43 months. Additionally, the richer economic level has the longest birth interval, i.e. 43.09 months. These results are in line with research conducted by [2], [15], [16], [34] with the consideration that the better the economic level of a family, the better access to health and knowledge.

Respondents mostly used modern methods (54.34%) as contraceptive methods, followed by no methods (38.74%) and traditional methods (6.92%). The use of contraception affects the interval between births where mothers with no method have the shortest interval of 33.13 months on average and vice versa for mothers with modern contraceptives, the longest interval is 46.54 months. This can happen because the effects of using contraceptives can delay the time until the next impregnation [2], [15].

Employment status has little effect on birth interval. It can be seen from the slightly different interval between working mothers (58.42%) and not working (41.58%). The birth interval for working mothers is 41.51 months, while for non-working mothers is 39.96 months. The birth interval for working mothers tends to be longer and this is normal [14].

Respondents who have had children but died have a much shorter birth interval than respondents whose children are still alive. From this study, it can be seen that for mothers who have given birth to children and died, the birth interval is 30.38 months, while mothers who give birth to children with live child status are 41.56 months. This is in line with research conducted by Kurniawati in which she explained the existence of a replacement effect. This effect results in mothers whose children die, they will immediately look for a replacement, namely by getting pregnant again [15].

Several sociodemographic characteristics as previously described indicate a correlation of several factors that affect birth spacing. Figure 1 shows a map of the distribution of the median birth distance for all provinces in Indonesia. It is seen that the darker the gradient, the longer the birth interval. Most of the eastern part of Indonesia has a short interval compared to the central and western parts of Indonesia. Several provinces included in the short birth interval category are Papua, West Papua, West Sulawesi, South Sulawesi, Maluku, East Nusa Tenggara, and North Sumatra. Many factors can cause these provinces to fall into the category of short birth intervals. One of them is the geographical condition where the provinces are far from the national capital. Especially Papua, in which access to health, education, and the economy are also still difficult. In line with the research by Hidayat, the research also focuses on birth intervals in the Papua region [14].

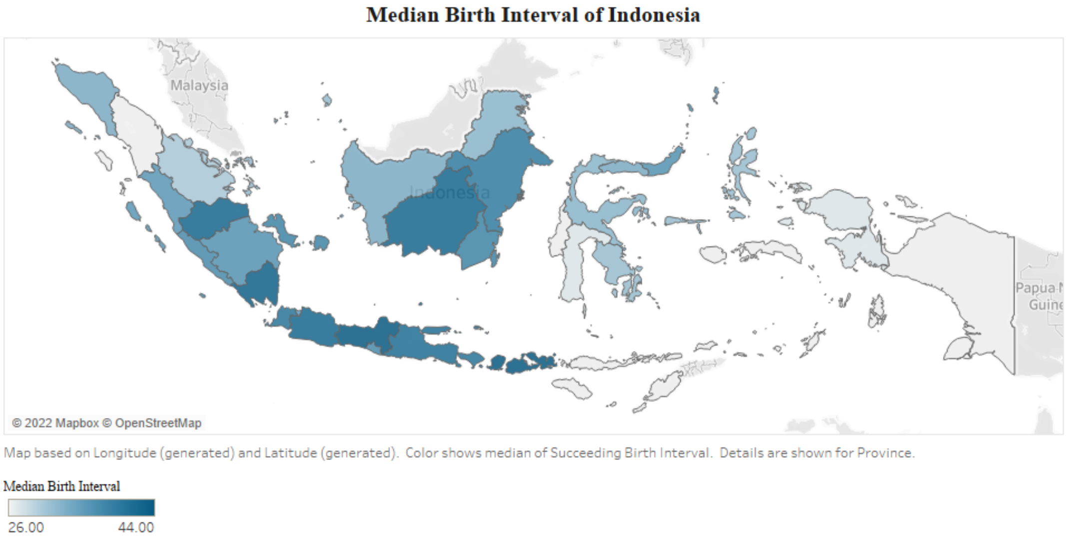

Figure 1. Distribution map of the median birth interval (in months) in Indonesia

Based on sociodemographic results, to get a normal birth interval, mothers need to get an education, and a fairly decent economy. In addition, the use of contraception also needs to be given. Regarding the status of working mothers, this can be returned to each mother considering that this is an option that can be discussed with the family. Mothers who lived in urban areas have better access to health, education, and the economy compared to mothers who live in rural areas. Likewise, correlate to the province where the mother lives, this requires cooperation with the government considering the equality of education, health, and economy that is received by all Indonesian people no matter where they lived.

Besides sociodemographic aspects, we classified short birth intervals using 4 machine learning algorithms, i.e. logistic regression, Naïve Bayes, SMO, and lazy LWL. The results of the goodness of the SBI classification model are shown in Table 2, Figure 2, and Figure 3. Table 2 presents the values of accuracy, precision, recall, and F-score for each algorithm. From these 4 score metrics, the values obtained are not too much different between algorithms. Naïve Bayes got the highest score for these 4 score metrics, with accuracy, precision, recall, F-score values of 0.891, 0.889, 0.891, and 0.885, respectively. On the other hand, the performance of the lazy LWL algorithm is not good enough seen from the lowest score metrics, namely for accuracy, recall, F-score, which are 0.854, 0.854, and 0.832, respectively.

In addition, to compare the performance of 4 algorithms from 4 score metrics, we measured the value of MCC, PRC area, and ROC area. The MCC results can be seen in Figure 2. The Naïve Bayes algorithm gave the highest MCC (0.687), whereas lazy LWL gave the lowest MCC (0.571). Overall, the order of classifiers with the best MCC is naïve Bayes, logistic regression, SMO, and lazy LWL. The result of the MCC is smaller than the previous performance metrics scores. It could be because MCC is suitable for imbalanced data in binary classification tasks. And on the other hand, MCC is more robust compared to other performance metrics. This is in line with the study that stated that MCC is way better to find the best performance of binary classification using a machine learning algorithm compared to accuracy and F1 score [33], [35].

Table 2. Accuracy, precision, recall, F-score for the four algorithms

Algorithms	Accuracy	Precision	Recall	F-Score
Logistic regression	0.862	0.858	0.862	0.854
Naïve bayes	0.891	0.889	0.891	0.885
SMO	0.860	0.855	0.860	0.852
Lazy LWL	0.854	0.867	0.854	0.832

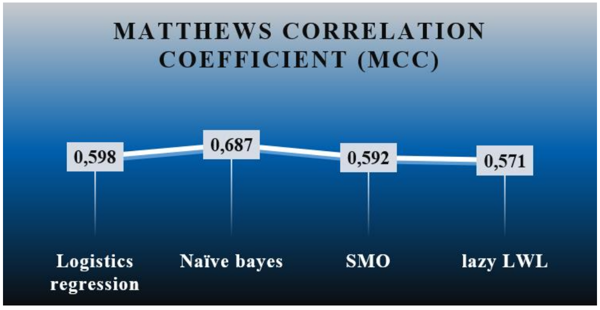

Figure 2. MCC for the four algorithms

The other two performance scores are PRC and ROC area which are shown in Figure 3. Of the 4 algorithms, Naïve Bayes gives the best performance with PRC and ROC area values are 0.960 and 0.972. Followed by lazy LWL with its area of PRC and ROC are 0.958 and 0.954. Then, the third-best algorithm is logistic regression with the area of PRC and ROC, i.e. 0.914 and 0.897. On the other hand, the SMO algorithm gets the worst performance with PRC and ROC area values of 0.793, 0.762 respectively. Following 7 performance metrics, we get the results that Naïve Bayes is the best classifier in classifying short birth intervals in the Indonesia DHS 2017 dataset. These results are in line with studies comparing several machine learning algorithms to predict individual survival. This study compares logistic regression, Naïve Bayes, and random forest and finds that Naïve Bayes is the best algorithm [36]. Furthermore, in this binary classification, we got the result that lazy LWL mostly performed the worst. This can happen because lazy LWL is suitable for the data stream. This has been revealed by research conducted for the detection of real-world network intrusion. The results showed that lazy LWL is good for data streams or big data [30].

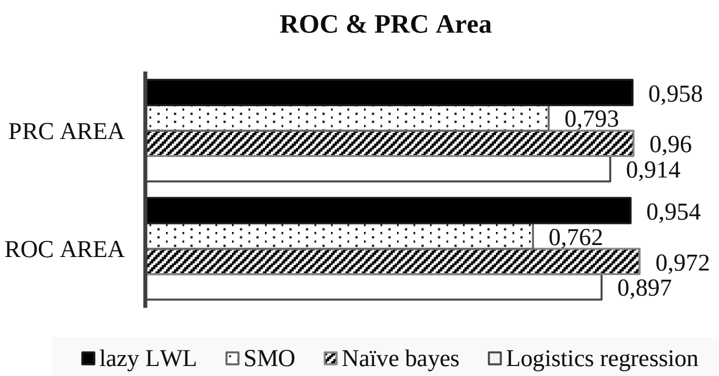

Figure 3. ROC and PRC area for the four algorithms

The confusion matrix is used to clarify the classification results for each category. Table 3 provides the confusion matrix for the 4 algorithms. We compared the actual number of events with the results of each classifier. The first classifier is Logistic regression which corrected classify SBI as much as 13.73%, corrected classify as not SBI is 72.51%, and incorrect classification equal to 13.76%. Continued to the Naïve Bayes classifier, the mothers who were classified as having children in an SBI were 15.79% and mothers who were correctly classified as not giving birth to children in close intervals were 73.31%. On the other hand, there is 10.90% for misclassification. SMO classify correctly to mothers who categorized as SBI as many as 13.88%, correctly classified as not SBI equal to 72.14%, and wrong classified 13.98%. The last classifier is lazy LWL which classify mothers categorized as SBI correctly is 10.29%, correctly classified as not SBI 75.11%, and misclassified equal to 14.60%.

Table 3. The number of actual and predicted outcomes

Classifier	Classification	Status	
		SBI	Not SBI
	Actual events number	8,286 (24.23%)	25,912 (75.77%)
Logistic regression	Correctly predicted outcome	4,696 (13.73%)	24,798 (72.51%)
	Incorrectly predicted outcome	1,114 (3.26%)	3,590 (10.50%)
Naïve bayes	Correctly predicted outcome	5,399 (15.79%)	25,071 (73.31%)
	Incorrectly predicted outcome	841 (2.46%)	2,887 (8.44%)
SMO	Correctly predicted outcome	4,747 (13.88%)	24,670 (72.14%)
	Incorrectly predicted outcome	1,242 (3.63%)	3,539 (10.35%)
Lazy LWL	Correctly predicted outcome	3,520 (10.29%)	25,686 (75.11%)
	Incorrectly predicted outcome	226 (0.66%)	4,766 (13.94%)

Through the confusion matrix, we can see the number of events classified using four classifiers. Each classifier gave different results to each other as well as different to the actual number of events. Naïve Bayes gave the closest result in classification the respondents similar with results of previous metrics score. Naïve Bayes gives the results that mothers who were classified as having children in an SBI were 5.399 or 15.79% and mothers who were correctly classified as not giving birth to children in close intervals were 25,071 or 73.31%. On the other hand, 2.887 or 8.44% of mothers who were wrongly classified as not giving birth to children in short birth intervals, while 841 or 2.46% of mothers who were misclassified gave birth to children in short birth intervals. Based on these results, we can provide input to the government, prospective parents, or parents who are planning to have more children to consider the distance between births. This is because, birth spacing that is too close will adverse to the mother, perinatal, neonatal, and child. In addition, the recommendation from WHO which states that the interval between births is at least 33 months can be considered.

4. CONCLUSION

The best classifier for classifying short birth intervals in Indonesia using the 2017 Indonesia Demographic and Health Survey data is Naive Bayes. From this classifier, it was found that for mothers classified as SBI as many as 15.79%, while those who were not classified as SBI were 73.31%. Although the results of the classification in the SBI are low, this value is quite large when considering the number of women of productive age (15–44 years) as many as 6,240 mothers who are classified into the category of short birth interval. If this continues, the health of the mother and newborn as well as siblings who have been born earlier can be compromised. Therefore, the role of the government is very much needed to make the right policy to obtain a normal birth interval according to WHO standards. In addition, the government also plays a role in equal distribution of education, health, and the economy so that mothers all around Indonesia have equal access to those facilities. In addition, knowledge about family health is needed, especially maternal and child health for prospective parents and parents who want to have children in the future.

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