Data Mining in Healthcare to Predict Cesarean Delivery Operations using a Real Dataset

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Abstract: In the digital era, the data revolution has become a significant part of every sector in society. The healthcare sector is one of the most vital parts of this revolution, as a massive amount of data is available, making medical case-related decisions critical. Hence, data-mining (DM) techniques are utilized to extract vital information and knowledge for decision-making. This study analysed data from cesarean delivery cases. A cesarean delivery operation generally takes place when there are challenges to normal delivery for several reasons or where normal delivery could cause potential complications in the future. In this paper, we have empirically examined several data-mining techniques for predicting the safest delivery type for both mother and child, using real cases taken from a health center in Tabriz. In addition, we used a cross-validation (CV) approach to evaluate the applied prediction models to ensure more realistic and reliable results. The naïve Bayesian (NB) classifier outperformed the other selected classifiers, with an accuracy rate of 65%. Available cesarean delivery operation data are rare, and increasing the cesarean case data is essential for better prediction.

1 INTRODUCTION

Recently, the advantages of data mining (DM) (Soleimanian et al., 2012) have been recognized in all disciplines and sectors, making DM a fixation in every field. DM helps extract useful information from huge data, as time and complexity are no longer an obstacle to achieve tasks. Health centers are collecting a massive amount of information about patients in order to raise health care quality by offering better services and medications that ensure patients' survival (Soleimanian et al., 2012), (Malik et al., 2018).

In the medical field, DM is an emerging research area. It is used for diagnosing (Malik et al., 2018) various diseases, such as breast cancer (Kumar et al., 2020), heart disease (Shammari et al., 2020), (Cherian & Bindu, 2017), lung cancer (Lynch et al., 2017), Parkinson's (Ramani & Sivagami, 2011), Alzheimer's (Tanveer et al., 2020)…etc, by feeding symptoms into the prediction model, which then predicts if the patient will test positive or negative.

DM is also used for prognosis, treatment planning (Malik et al., 2018) and medical images and statistical data, which are examined for medical decisions.

In the late 19th century, a dramatic increase occurred throughout the world in the rate of cesarean delivery operations (Rokach & Maimon, 2005). The World Health Organization (WHO) defined trends in cesarean delivery operations through the years (i.e., 1983–2017; see Figure 1) (World Health Global Health Observatory Data Repository, 2010).

Figure 2 shows the density of the rate of cesarean delivery operations per country (Ana Pilar Betrán, Jianfeng Ye, Anne-Beth Moller, Jun Zhang, A. Metin Gülmezoglu, 2016).

Meanwhile, medical committees and governments have sought to reduce the rates of cesarean delivery operations by introducing policies that promote vaginal delivery, often with little focus on the potential consequences of these recommendations (Dietz HP, 2016).

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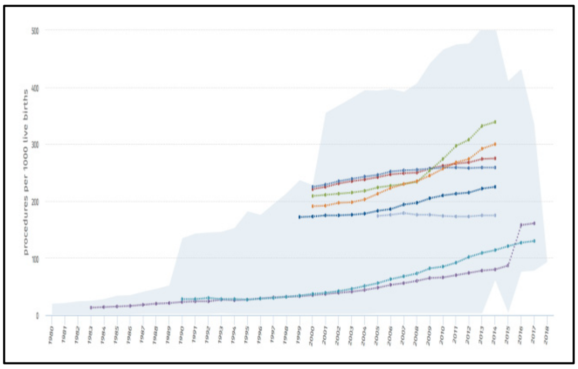

Figure 1: The rate of cesarean deliveries over the years (World Health Organization global health observatory data repository, 2010).

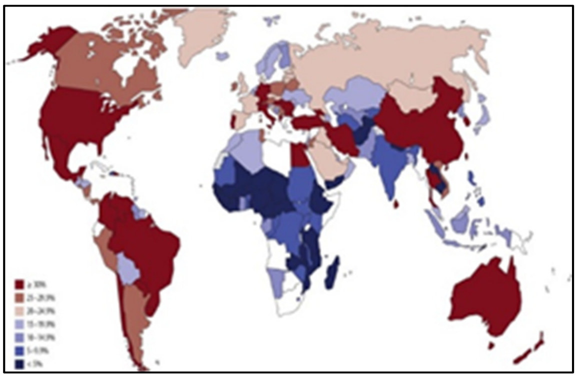

Figure 2: the rate of cesarean deliveries by country (Ana Pilar Betrán, Jianfeng Ye, Anne-Beth Moller, Jun Zhang, A. Metin Gülmezoglu, 2016).

Doctors usually desire a safe delivery for a pregnant woman, unless an urgent condition forces the need for a cesarean delivery. Many situations call for cesarean delivery, some of which are serious, including the occurrence of critical situations or the avoidance of serious problems, while others have no medical indications (Gee et al., 2020), (Hernández-Martínez et al., 2016), (Bailit et al., 2004). The ongoing improvement of medical technology have made surgeries safer than before, but the risk of such decisions remains a hazard for both mother and baby (Gee et al., 2020) and is not encouraged by doctors. In serious cases, such decisions should be based on clear and potentially life-threatening indications. Furthermore, deciding in advance instead of making a sudden decision will help prepare the patient, clinic, and hospital.

In this paper, we recognize such a need and believe in the importance of having a medical staff that is aware of the mode of delivery in advance for the safety of both mother and baby, especially when serious indicators are present. Therefore, we aim to predict the delivery type (i.e., cesarean or not) based on significant factors that affect the mother's health, like blood pressure and heart status. We use the cesarean dataset from the Tabriz health center (Soleimanian et al., 2012) and employ different prediction models to train the dataset, such as naïve Bayesian (NB) (Parlina et al., 2019), support vector machine (SVM) (Yao et al., 2013), k-nearest neighbor (kNN) (Deng, Z., Zhu, X., Cheng, D., Zong, M., & Zhang, 2016), OneR (Jamjoom, 2020), decision tree-J48 (DT-J48) (Sharma et al., 2013) and decision tree-random forest (DT-RF) (Ali et al., 2012). These classifiers have used cross-validation (CV) with a 10-fold approach (Geisser, 1975) to test and evaluate the accuracy of the prediction and other selected evaluation metrics for each of them.

The rest of the paper is organized as follows: Section 2 introduces related work, Section 3 describes the methodology and its results, and Section 4 concludes the study.

2 RELATED WORK

Many studies in the healthcare domain have used DM techniques to predict cesarean delivery operations. For example, (Soleimanian et al., 2012) used a decision tree (DT) classifier as a prediction model. In (Soleimanian et al., 2012), the authors used the extension of Quinlan's induction decision tree (ID3) (Quinlan, 1986) which is a C4.5 algorithm, due to its ability to build different trees with different strategies and high accuracy in diagnosis. They developed a pregnancy dataset collected from the Tabriz health center and produced a model with an accuracy rate of (86.25%). The complexity of the tree generated was large; its depth was 31, and it had 21 leaves. Large trees are costly and may yield poor generalizations (Rokach & Maimon, 2005). The authors recommended increasing the dataset and adding more related attributes in order to improve accuracy. Similarly, (Amin & Ali, 2018) used the same dataset as (Soleimanian et al., 2012) but different prediction models—namely, SVM, RF, NB, kNN, and logistic regression (LR)—resulting in accuracies of 76.3%, 95%, 76.3%, 95%, and 77.5%, respectively. The results showed that RF and kNN were the best in performance. The main concern with the study is the use of the whole dataset for training and testing at the same time, as the results are likely to be unrealistic because data must be tested using unknown cases to the classifier or the result will be extremely positive (Frank et al., 2016).

In (Dulitzki et al., 1998) the researchers created a prediction model using linear regression (LR) to predict the cesarean delivery rate and its factors for pregnant women aged 44 years and above. They identified several attributes that were significant for accurate prediction, including age, parity, and pregnancy difficulties. The study emphasized the high risk of cesarean delivery when the mother was at least 44 years old.

The study of (Sims et al., 2000) applied half of the samples on each DT rule-based and LR classifiers to train a predictive model for cesarean delivery prediction and kept the remaining samples as a testing set. The two classifiers used similar attributes. Six different DT were examined. The authors concluded that both DT and LR had comparable results, but DT was simpler and better at handling missing values. Moreover, both algorithms were consistent in terms of determining the important risk factors.

A study to explore the various changes in the causes of cesarean delivery was conducted by (Bailit et al., 2004), using a dataset collected from all birth transactions in North Carolina in 1995, 1997, 1999, and 2001 to create a model using an LR algorithm for cesarean delivery prediction. The study identified an increasing trend in the rate of cesarean delivery due to changes in clinician and hospital behavior as well as a new demand for elective cesarean delivery. The model used various risk factors as attributes, including age, race, gestational age, multiple pregnancy, complications, and severity of medical conditions. The model found that complications, nulliparity, and multiple gestations were the most significant attributes. The authors recommended further investigation about the causes of cesarean delivery to explain the increase. In the same context, more investigations regarding the risk factors of cesarean delivery were discovered by (Hernández-Martínez et al., 2016). The authors used a multivariate analysis with binary LR and receiving operating characteristics (ROC) metric to predict power determination. The values of maternal, obstetrics, fetal, and gynecologist attributes were collected from one of Spain's hospitals for three years, from 2009 to 2011, and were used to train the predictive models. The models succeeded in discriminating the risk of cesarean delivery; such results can be helpful in decision making.

More studies on the risk factors of cesarean delivery were done by (Schiff & Rogers, 1999) particularly on American Indian women in New Mexico, who have a smaller cesarean delivery rate compared to other populations in the United States. The authors believed that ethnicity had an effect on this difference. They studied demographic, prenatal, and intrapartum factors to detect risk factors for cesarean delivery but found nothing specifically different with American Indian women in New Mexico, who have the same risk factors for cesarean delivery as other populations.

The authors in study (Burke et al., 2017) assessed five attributes affecting the risk of cesarean delivery and built a predicting model (i.e., multiple LR analysis and mathematical modelling) to detect a pregnancy threatened by an unplanned cesarean delivery. Such models help improve the service quality of the hospital and reduce patient risk.

Finally, (Al Housseini et al., 2009) compared two prediction models, LR and neural network (NN), to predict the delivery mode for nulliparas. They used some maternal and fetal clinical attributes of obstetric patients from 2005 to 2007. They determined that NN was slightly better in performance as it achieved an accuracy of 53%, which was higher than LR and what has been achieved by prior studies. Generally, NNs are successful when used for clinical problems that can be solved by mathematical methods and can be improved by practice; their only limitation is that they do not address the size of the effect for individual variables.

3 METHODOLOGY

The dataset for conducting this study was based on the existing dataset collected by the healthcare center located in Tabriz (Soleimanian et al., 2012). The dataset contained information on 80 real cases; each case had five values for the five most important attributes for the binary classification problem and the cesarean delivery problem. Table 1 summarizes the dataset's attributes. The analysis was performed using Waikato Environment for Knowledge Analysis (WEKA) software (Waikato, 2018), (Garner, 1995) to train and test the dataset on different prediction models—specifically, NB (Parlina et al., 2019), SVM (Yao et al., 2013), kNN (Deng, Z., Zhu, X., Cheng, D., Zong, M., & Zhang, 2016) where k=3, OneR (Jamjoom, 2020), DT-J48 (Sharma et al., 2013) and DT-RF (Ali et al., 2012).

Table 1: Attributes description of cesarean dataset.

Attribute	Description	Value
Age	Maternal age	numeric
Delivery number	Number of births	numeric
Delivery time	The normal delivery time for the pregnant woman after completing 37 weeks (i.e., timely). Delivered before that considered premature, after 40 weeks considered latecomer	Premature, Timely, Latecomer
Blood of Pressure	Measurement of Blood pressure	Low, Normal, High
Heart Problem	Heart status of the pregnant woman	Apt, Inept
Cesarean	The classification of the pregnant woman to deliver with cesarean operation or vaginal	yes, no

3.1 Experiment Results

To test and validate the trained models, we used CV with a k-folds approach (Geisser, 1975), and made k equal to 10. CV was one technique used to evaluate the performance of the prediction model on a certain dataset and estimate the error of the classifier (Anguita et al., 2012), (Wong, 2017). It divided the dataset into equalized number of k subsets, then (k-1) subsets were repeatedly trained and the remaining subset used to validate the performance of the classifier (Geisser, 1975), (Anguita et al., 2012). In other words, it resampled the training and test subsets in each training iteration, and the final accuracy achieved was the average of the total k accuracies for all iterations. The test subset contained instances not seen by the model during the training phase, which can help obtain a reliable estimation of the classifier performance (Wong, 2017) as CV's approach helps reduce generalization errors and variance (Anguita et al., 2012). CV gives a realistic estimation because, in reality, the model predicts real cases that the model may have never seen in the training phase. Using the whole dataset for training and testing at the same time may generate unrealistic results that are extremely positive and prone to overfitting (Mitchell, 1997).

Furthermore, we used the accuracy of each classifier that shows the rate of cases predicted correctly to compare between the models. Accuracy was calculated using equation 1:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

where TP, TN, FP, and FN are the elements of the confusion matrix (Basu & Murthy, 2012), (Fawcett, 2004) and the base for calculating many metrics for classifier evaluation. Figure 3 shows the confusion matrix for all applied classifiers in this study along with actual values for TP, TN, FP, and FN.

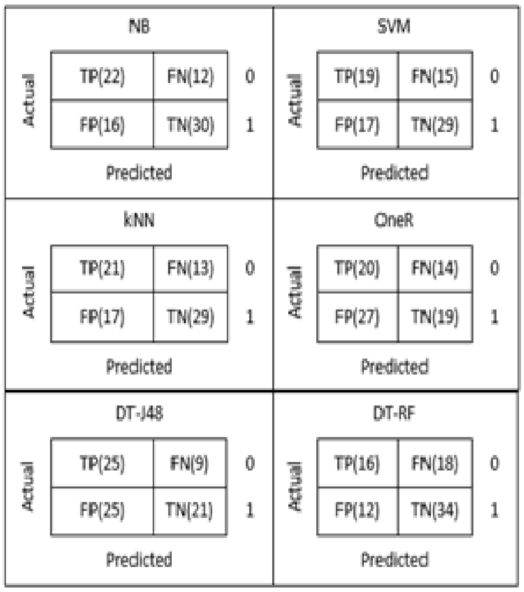

Figure 3: The confusion matrix for the applied classifiers.

We also calculated other evaluation metrics for the applied classifiers, such as precision, recall, f-measure, correctly classified instances, misclassified instances, total number of instances. and time consumed to build the model. We used equations 2, 3, and 4 to calculate precision (i.e., percentage of correctly observed positive cases), recall (i.e., percentage of correctly predicted real positive cases) and f-measure, respectively. The results are presented in Table 2.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{F-measure} = \frac{2*(\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})} \quad (4)$$

Moreover, we evaluated the strength of the relationship between the class and other attributes—that is, the correlation (Trabelsi et al., 2017) between the class and each attribute in the dataset. Attributes with a high positive value indicated the influence of the class value. Table 3 shows the correlation values for each attribute. A strong relationship emerged between the class and the "heart problem," which means that the pregnant woman's heart status has a strong influence when making decisions regarding the need for a cesarean delivery or not.

Table 2: The performance evaluations of the applied classifiers.

Metric	NB	SVM	kNN	OneR	DT-J48	DT-RF
Accuracy	65 %	60 %	62.5 %	48.75 %	57.5 %	62.5 %
Precision	0.657	0.603	0.632	0.512	0.615	0.619
Recall	0.650	0.600	0.625	0.488	0.575	0.625
F-Measure	0.652	0.601	0.627	0486	0.571	0.618
Correctly Classified Instances	52	48	50	39	46	50
Misclassified Instances	28	32	30	41	34	30
Total Number of Instances	80	80	80	80	80	80
Time to build the model (secs.)	0.03	0.33	0	0	0.08	0.46

Table 3: Attributes analysis.

Attribute	Correlation
Age	0.1001
Delivery number	0.0657
Delivery time	0.151
Blood of Pressure	0.2393
Heart Problem	**0.3526**

3.2 Results and Discussion

This section discusses the experimental results and how each classifier was accurately applied to predict the cesarean delivery. Table 2 shows that NB outperformed all the applied classifiers, as it was able to correctly classify the unseen cases with an average accuracy rate of 65%; this was followed by kNN and DT-RF, with an average accuracy of 62.5%, and SVM, DT-J48, and OneR, with 60%, 57.5%, and 48.75%, respectively (see Figure 4). Regardless, NB was the best classifier among the applied classifiers, although the difference between the applied classifiers was not large. If we do not consider the OneR classifier, the difference is only about (7.5%).

Comparing these results with those of (Soleimanian et al., 2012) and (Amin & Ali, 2018), the current study achieved less accuracy than the other studies, but using the CV approach and evaluating the performance of the classifiers based on unseen cases yields realistic and reliable results, unlike in the other studies, which based their evaluations only on training sets. However, the low accuracy can be due to the limited number of cases for training and testing. Enriching the dataset with more real cases will improve the generalization and, thus, the performance of the classifiers. The values of the recall in all applied classifiers also reflects the insufficiency in the datasets available for accurate prediction. Therefore, enriching it is necessary.

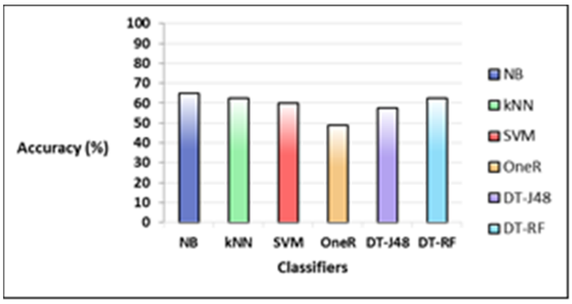

Figure 4: The average accuracy of the applied classifiers.

Moreover, the values of precision among the applied classifiers were very close to each (except OneR). Precision usually explains how much the predictive power of the classifier is.

The attribute analysis presented in Table 3 indicates that the "heart problem" attribute is the strongest attribute correlated with the class attribute, with a correlation value equal to 0.35. Yet the value is far from the optimal correlation's value of 1. This opens a new research area to investigate to determine the most significant factor (i.e., attribute) that highly affects cesarean delivery prediction.

Using the CV approach to evaluate the classifiers by testing each of them with unseen cases gives strength and reliability to the study, as this is often the case in reality. CV decreases the variance in the prediction model over the k subsets.

4 CONCLUSIONS

DM is useful in healthcare organizations, especially when critical decisions are needed for the safety of the mother and child, such as when a doctor decided to conduct a cesarean delivery instead of a vaginal delivery. Predicting the delivery mode within an appropriate amount of time is important so both medical staff and the mother will be appropriately prepared. In this study, we used the medical information of 80 pregnant women from the health center in Tabriz to predict the delivery mode using several classifiers: NB, SVM, kNN, OneR, DT-J48, and DT-RF. The results showed that NB achieved the best accuracy, with an average accuracy rate of 65%. The results are reliable and close to realistic due to using the CV approach when evaluating the classifier performance. The CV approach uses unseen cases to test the classifier, which is more realistic. Future research should improve the accuracy of the existing dataset by enriching the dataset with more real cases. Moreover, more attributes that are significant in such prediction should be investigated.

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