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Machine Learning Model Aid Prediction for Failed Nonoperative Reduction of Intussusception

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Abstract. The occurrence of imbalanced class in a dataset causes the classification results to tend to the class with the largest amount of data (majority class). A sampling method is needed to balance the minority class (negative class) so that the class distribution becomes balanced and leading to better classification results. This study was conducted to overcome imbalanced class problems on the Nonoperative reduction of intussusception dataset using ADASYN, SMOTE-NC and k-means-SMOTE. The dataset has 173 instances of the positive class (majority class) and 79 instances of the negative class (minority class) by comparing the classification (Logistic Regression, SVM, and Decision Tree) while implementing Decision Tree with SMOTE-NC Oversampling and Decision Tree with K-means SMOTE Oversampling has the highest accuracy of 94%, while Support Vector Machine with Non-Oversampling produces the highest sensitivity of 100%

Keywords: Machine Learning, Logistic Regression, Support Vector Machines, Decision Trees, Intussusception, Non-operative Reduction, ADASYN, k-means-SMOTE, SMOTE-NC, SMOTE, classification performance, class imbalance

1 Introduction

This article is part of an independent study on Machine Learning model aid prediction for failed nonoperative reduction of intussusception The objectives of the study are to study the use of machine learning models to predict medical data and study the efficiency of using algorithms to increase the amount of medical data without causing the data to be biased towards any one point. The study results prediction with Non-Oversampling Logistic Regression has highest accuracy and sensitivity of 80% and 86%. However, prediction with Oversampling has performs significantly better. The method of Oversampling that gives dominant performance is K-means SMOTE, and the classification model that gives the most accuracy is Decision Tree. When applying the machine learning model and the Oversampling method, Decision Tree with SMOTE-NC Oversampling and Decision Tree with K-means SMOTE Oversampling has supreme accuracy of 94%, and Support Vector Machine with Non-Oversampling has elevated sensitivity of 100%

2 Literature Review

Intussusception [1] [2] is a condition where the small intestine telescopes into the large intestine, causing abnormal compression of the intestines. This leads to symptoms such as abdominal pain, vomiting, palpable abdominal mass, and bloody stools. It is commonly found in children aged 3 months to 3 years. There are two treatment approaches: surgical and non-surgical. This article focuses specifically on the non-surgical treatment of intussusception.

A machine learning model [3] [4] is a tool used to analyze and predict outcomes (class/label) by examining various factors in the data through mathematical equations. In this research, the chosen tool falls under the category of classification, a type of supervised learning. Three machine learning models will be employed for analysis: 1.) Logistic Regression [5] [6] [7] is a statistical method used for binary classification, predicting the probability of an event occurring. It models the relationship between the dependent variable and one or more independent variables, providing insights into the likelihood of an outcome. 2) Support Vector Machines (SVM) [8] [9] is a supervised learning algorithm used for classification and regression tasks. It works by finding a hyperplane that best separates data points into different classes while maximizing the margin between them. 3) Decision Trees [10] [11] is a tree-like model in machine learning used for classification and regression. It recursively splits the data based on features to create decision nodes, facilitating effective predictions and interpretability.

Imbalanced data [12] [13] [14] [15] occurs when the distribution of classes in a machine learning dataset is uneven, posing challenges for model training. Undersampling addresses this by reducing the size of the majority class, while oversampling involves increasing the instances of the minority class to achieve a more balanced dataset, aiding in better model performance.

In this article used 3 Oversampling method: 1) ADASYN (Adaptive Synthetic Sampling) [16] is an oversampling technique designed to address class imbalance in machine learning datasets. It focuses on generating synthetic examples for the minority class, with emphasis on challenging instances. ADASYN adapts its synthetic sample creation based on the local density of instances, aiming to enhance model performance in handling imbalanced data. 2) SMOTE-NC (SMOTE for Nominal and Continuous features) [17] [18] is an extension of the traditional SMOTE algorithm designed to handle datasets with both nominal and continuous features. It intelligently synthesizes minority class instances by considering the distinct characteristics of nominal and continuous attributes, improving the effectiveness of oversampling in imbalanced datasets. 3) K-Means SMOTE [17] [19] is an oversampling technique that combines K-means clustering with the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. It identifies clusters in the minority class and applies SMOTE to generate synthetic samples, promoting better representation of minority instances in the dataset and improving machine learning model performance.

2.1 Intussusception

Khorana, J. et al. proposed an article titled "*Clinical prediction rules for failed non-operative reduction of intussusception*" [20]. The study aimed to develop a scoring system for predicting the failure of non-surgical treatment for intussusception using various factors. The findings suggest that the scoring system effectively predicts the likelihood of treatment failure for non-surgical management of intussusception. This scoring system is designed to inform parents of children with intussusception about the risk of treatment failure, serving as a guideline for decision-making. The scoring system assigns points based on factors such as weight, with scores indicating the probability of treatment success or failure. A higher total score implies a higher likelihood of failure, providing parents with insights for making informed decisions about future treatment.

Table 3 Item scoring scheme for predictors for failure reduction of intussusception derived from coefficients of selected indicators

Risk indicators	Coefficients	Transformed coefficients	Assigned score
Weight			
≤12 kg	0.39	1.70	2
>12 kg	–	–	0
Duration of symptoms			
≤48 hours	–	–	0
>48 hours	0.23	1	1
Vomiting			
No	–	–	0
Yes	0.49	2.13	2
Rectal bleeding			
No	–	–	0
Yes	0.41	1.78	2
Abdominal distension			
No	–	–	0
Yes	0.47	2.04	2
Temperature >37.8°C			
No	–	–	0
Yes	0.41	1.78	2
Palpable mass			
No	–	–	0
Yes	0.23	1	1
Location			
Right	–	–	0
Left	0.39	1.70	2
Ultrasound (poor prognosis sign)			
No	–	–	0
Yes	0.30	1.30	1
Method of reduction			
Pneumatic	–	–	0
Hydrostatic	0.29	1.26	1

Figure 1 CMUI [20]

Boonsanit, K. et al., in their article "*Validation and modification of the 'Chiang Mai University Intussusception scoring system' used to predict failure of non-surgical treatment in infantile intussusception*" [21], found that the CMUI scoring system's non-surgical treatment for intussusception in children has been modified to enhance its reliability in predicting outcomes. The study indicates that the revised scoring system provides improved predictions, aiding parents in making informed decisions about the potential success or failure of non-surgical treatment.

Upon reviewing related literature on intussusception, it is evident that numerous studies, both in Thailand and internationally, focus on the non-surgical treatment of intussusception. This approach is preferred due to its lower risk, reduced likelihood of failure, shorter treatment duration, and minimal recovery time. It provides valuable information for parents to make decisions about their child's treatment.

Additionally, research has explored the use of machine learning (ML) models to predict intussusception treatment outcomes. For instance, the study by Jing-Yan Guo and Yu-Feng Qian titled "*Predicting recurrent cases of intussusception in children after air enema reduction with machine learning models*" [22] revealed that XGBoost demonstrated the highest accuracy (71.8%), followed by Logistic Regression (65.2%), and Support Vector Machine (61.3%) in predicting recurrent intussusception cases.

Considering the imbalance in data, ML models have been applied to address the increasing complexity of prediction factors. The use of ML models not only enhances prediction accuracy but also tackles the issue of imbalanced data by incorporating data augmentation. This approach not only supports a more detailed prediction process but also contributes to handling the scarcity of difficult-to-obtain data.

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2.2 Oversampling in Medical data

Medical data is often challenging to obtain, limited in quantity, and features imbalanced response types, where one type (majority) is more prevalent than the other (minority). In the article "K-means-SMOTE for handling class imbalance in the classification of diabetes with C4.5, SVM, and naive Bayes" [23], it was found that employing K-means-SMOTE effectively addressed the issue of imbalanced data in diabetes classification. Among the models, Support Vector Machine exhibited the highest accuracy (82%) and sensitivity (87%). The researchers suggested further exploration by incorporating additional data augmentation methods for a comprehensive comparison, including pairing with different ML models. The study considered three data augmentation methods, three ML models, and a control group without data augmentation, aiming to compare accuracy and sensitivity. This approach serves as an alternative for utilizing ML models in medical settings with imbalanced data.

3 Data and Methodology

3.1 Data

Patients aged 0-15 years diagnosed with intussusception was admitted to the Pediatric Surgery Department Maharat Nakorn Chiang Mai Hospital Faculty of Medicine Chiang Mai University between 2006 – 2020.

3.2 *Pre-processing*

Select feature are Type of intussusception, Gender, Age, Body weight, Duration of symptoms, Vomiting, Bloody stool/Rectal bleeding, Abdominal distension, Body Temperature, Palpable abdominal mass, Location of intussusception, Method of reduction, Small bowel obstruction from Plain film Abdomen , a thick peripheral hypoechoic rim, free intraperitoneum fluid, fluid trapped within intussusceptum, enlarged lymph node in intussusception, pathologic lead point, absence of blood flow in the intussusception, Successful reduction and using one hot encoder for category data

3.3 *Evaluation indicators*

In this IS, Accuracy and Recall or Sensitivity were chosen as indicators for the evaluation of the model. If models equal accuracy, it was also used Recall or Sensitivity to consider.

4 SUMMARY

Oversampling	Model	Accuracy	Precision	Recall	F1-Score
Non-Oversampling	Logistic Regression	0.80	0.86	0.86	0.86
	SVM	0.71	0.71	1.00	0.83
	Decision Tree	0.67	0.77	0.75	0.76
ADASYN	Logistic Regression	0.75	0.93	0.69	0.79
	SVM	0.61	0.75	0.67	0.71
	Decision Tree	0.90	0.94	0.92	0.93
SMOTE-NC	Logistic Regression	0.76	0.90	0.75	0.82
	SVM	0.45	0.79	0.31	0.44
	Decision Tree	**0.94**	**0.97**	**0.94**	**0.96**
K-means SMOTE	Logistic Regression	0.80	0.88	0.83	0.86
	SVM	0.67	0.69	0.94	0.80
	Decision Tree	**0.94**	**0.97**	**0.94**	**0.96**

Figure 2 Result

In this IS, the study results prediction with Non-Oversampling Logistic Regression has highest accuracy and sensitivity of 80% and 86%. However, prediction with Oversampling has performs significantly better. The method of Oversampling that gives dominant performance is K-means SMOTE, and the classification model that gives the most accuracy is Decision Tree. When applying the machine learning model and the Oversampling method, Decision Tree with SMOTE-NC Oversampling and Decision Tree with K-means SMOTE Oversampling has supreme accuracy of 94%, and Support Vector Machine with Non-Oversampling has elevated sensitivity of 100%

5 DISCUSSION

Increase the collection of various factors, such as the impact of blood tests. Since this research did not include factors from blood tests, it is suggested that future research consider adding factors related to blood results or other additional factors.

Data Quantity: If possible, it is advisable to increase the amount of data or collect a larger dataset. Improve the model annually or find ways to increase the population size of the data. In this study, the researchers attempted to calculate a necessary population of approximately 3000 samples, but when the model was constructed, it was not possible to increase the population as much as desired, only by about 300 samples.

Improving Oversampling methods or Machine Learning models to enhance accuracy, sensitivity and model suitability for the data format.

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