ORIGINAL ARTICLE

Predicting surgical intervention in pediatric intussusception using machine learning model

Facteurs prédictifs d'intervention chirurgicale lors d'une invagination intestinale aigue chez l'enfant suivant un modèle d'apprentissade automatique

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Abstract

Aim: To develop and validate a model predicting surgical treatment of intussusception in children.

Methods: Design: Retrospective study of charts and development of a model for predicting surgical treatment using logistic regression and machine learning using''Knime'' platform. Setting: Data collection occurred in the Department of Pediatric Surgery between January 2013 and December 2022. Patients: Children aged less than 3 years old with the diagnosis of ileocolic intussusception.

Results: One hundred and nine children were assigned to the training set, and 47 were assigned to the validation set. There were no significant differences between the two sets in clinical characteristics and surgical reduction. Surgical reduction was performed in 64 patients in the training set and 23 patients in the validation set (p=0.259). The univariate analysis showed that the duration of symptoms, mental state, palpable abdominal mass, bloody stools, elevated white blood cells, intraperitoneal effusion on ultrasound, and mass length were significantly associated with surgical treatment. After Logistic regression, bloody stools (p=0.033; OR=2.61), the duration of symptoms (p=0.028; OR=1.02), and the length of the intussusception (p=0.014; OR=1.265) were identified as independent risk factors for surgical treatment. The clinic-pathologic risk factors incorporated in the machine learning model were bloody stools, the duration of symptoms, and the length of the intussusception. This model was highly predictive, with a sensitivity and specificity of 95% for the SVM-derived model.

Conclusions: This model may be applied to facilitate pre-surgery decisions for children with intussusception. Larger prospective multicenter studies are needed to validate the model.

Key words: intussusception, prediction, surgery, machine learning model

Résumé

Objectif: Développer et valider un modèle de prédiction du traitement chirurgical de l'invagination intestinale chez l'enfant.

Méthodes: Conception : Étude rétrospective des dossiers et développement d'un modèle de prédiction du traitement chirurgical en utilisant la régression logistique et l'apprentissage automatique via la plateforme "Knime". Cadre : Département de Chirurgie Pédiatrique entre janvier 2013 et décembre 2022. Patients : Enfants de moins de 3 ans ayant une invagination iléocolique.

Résultats: Cent neuf enfants ont été assignés au groupe d'entraînement, et 47 à celui de validation. Il n'y avait pas de différences significatives entre les deux groupes concernant les caractéristiques cliniques et la réduction chirurgicale. La réduction chirurgicale a été réalisée chez 64 patients dans le groupe d'entraînement et 23 patients dans celui de validation (p=0,259). L'analyse univariée a révélé que la durée des symptômes, l'état mental, la masse abdominale, la rectorragie, l'hyperleucocytose, l'épanchement intrapéritonéal et la longueur de la masse étaient significativement associés au traitement chirurgical. Après la régression logistique, la rectorrgie (p=0,033 ; OR=2,61), la durée des symptômes (p=0,028 ; OR=1,02) et la longueur du boudin (p=0,014 ; OR=1,265) étaient prédictifs pour le traitement chirurgical. Ces facteurs de risque clinicopathologiques ont été intégrés dans le modèle d'apprentissage automatique. Ce modèle s'est révélé hautement prédictif: une sensibilité et une spécificité de 95 % pour le modèle dérivé de SVM.

Conclusions: Ce modèle peut être appliqué pour faciliter les décisions préopératoires pour les enfants atteints d'invagination intestinale. Des études multicentriques prospectives de plus grande envergure sont nécessaires.

Mots clés: inveagination intestinale, prediction, chirurgie, modèle d'apprentissage automatique

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Introduction

Intussusception is a critical abdominal emergency that predominantly affects infants and preschool-aged children. This condition is characterized by the telescoping or invagination of one segment of the bowel into another, typically involving the proximal segment being pulled into the distal segment. Its incidence is estimated to occur in approximately 1 to 4 out of every 2000 infants and children [1-3]. Timely diagnosis and intervention are of paramount importance to prevent potential complications and minimize morbidity associated with intussusception [1-4]. The management of intussusception encompasses a spectrum of treatment options, ranging from non-invasive procedures to surgical interventions [5]. For non-surgical interventions, the preferred method is pneumatic or hydrostatic reduction, which involves the gentle inflation of the intestine to correct the invagination. However, the success rate of these non-surgical procedures can vary widely, ranging from 46% to as high as 94% based on data available in the medical literature [1, 5-7]. In cases where non-operative reduction is contraindicated or proves unsuccessful, surgical intervention becomes necessary to resolve the condition.

Extensive research has been conducted to identify the risk factors associated with the need for operative treatment in cases of intussusception [1, 2, 3, 8-11]. These risk factors may include clinical signs, imaging findings, and patient demographics. In the realm of medical practice, clinical prediction tools have gained prominence, similar to those employed in the management of other conditions such as appendicitis [12,13]. These tools are defined as clinical decision-making instruments that amalgamate clinical history, physical examination findings, biological parameters, and imaging results to predict specific outcomes, stratify patients by risk, or guide diagnostic and therapeutic approaches [3, 8, 12-14]. Their primary objectives are to standardize patient treatments and concurrently enhance the quality of counseling provided to patients and caregivers, all with the overarching goal of improving patient outcomes.

However, despite the progress made in this field, there still exists a notable gap when it comes to the availability of accurate predictive tools and the validation of their effectiveness in the context of pediatric intussusception. Hence, the central objective of our study is to undertake the development and subsequent validation of an artificial intelligence (AI) model that can effectively predict the necessity of surgical intervention in cases of pediatric intussusception. Such a model holds the potential to significantly enhance the clinical management of this condition by providing healthcare practitioners with an additional tool to aid in making timely and well-informed treatment decisions, ultimately leading to improved patient outcomes and reduced morbidity.

Methods

Patients and study design

We conducted a retrospective study involving children aged less than 3 years old diagnosed with first time ileocolic intussusception, confirmed by ultrasound (US) performed by experimented radiologists, and hospitalized in the Department of Pediatric Surgery at Hedi Chaker Hospital. The study spanned from January 2013 to December 2022, and ethical consent was obtained from the local board. Exclusion criteria were patients with peritonitis needing immediate surgical exploration, recurrent cases, and patients with insufficient data in their hospital charts. Approval for this study was obtained from the hospital's ethics committee. Due to the retrospective nature of the study, the requirement for informed consent was waived.

Data Collection

Collected variables included Clinical, ultrasonographic, and laboratory tests.

Clinical Parameters were gender, age, weight, temperature, vomiting, duration of abdominal pain, presence of an abdominal mass, occurrence of bloody stools, duration of symptoms, the season of presentation, and infection history (specifically, respiratory or digestive symptoms in the preceding week such as cough, rhinorrhea, and diarrhea), as well as mental state.

Ultrasonographic features were the long-axis diameter of the intussusception, its location, the presence of enlarged lymph nodes, the absence of blood flow within the mass, and the presence of free intraperitoneal fluid.

Laboratory Tests included white blood cell count (WBC), C-reactive protein (CRP) levels, serum sodium (Na^+), serum potassium (K^+), and serum chloride (Cl^-).

Statistical Analysis

We conducted our statistical analyses using IBM SPSS Statistics 20. Additionally, for the development of our machine learning models, we used the ''Knime'' platform. Initially, we performed a comprehensive analysis of clinical, ultrasonography, and laboratory test variables using descriptive statistics, providing a comprehensive overview of our dataset. Categorical data were summarized as absolute values and percentages, while continuous data were presented as median values with their respective ranges. To investigate factors associated with surgical intervention, we divided patients into surgery and non-surgery groups. We conducted both univariate and multivariate analyses to identify independent factors relevant to surgical intervention. Continuous variables with a normal distribution were analyzed using the Student's t-test, and countable variables were assessed using the chi-squared test. A logistic binary regression model was employed to determine predictive factors for surgery, with data included in the model if they were statistically relevant in the bivariate analysis or well-described in the literature. The backward conditional regression method was used for model refinement.

The machine learning model aimed to predict the risk of surgery based on independent factors identified following logistic regression analysis. This model holds significant potential to enhance predictive accuracy within our study. To ensure the robustness of our machine learning model, we randomly divided the patient cohort into training and validation datasets at a 7:3 ratio. The training set was utilized to train the prediction model, while the validation set served to assess the model's performance and predictive accuracy. The sensitivity and specificity of our machine learning model were evaluated using the "SCORER" tool available on the ''Knime'' platform, providing valuable insights into its overall performance. ROC curve analysis was also used for perfomance evaluation. A significance level of $p < 0.05$ was considered statistically significant. This threshold allowed us to draw meaningful and confident conclusions from our data.

Results

Patients and operative characteristics

A total of 165 children aged less than 3 years with confirmed ileocolic intussusception were admitted to the pediatric surgery department. Six patients with insufficient medical information and 3 patients with initial pneumo-peritoneum were excluded from the study. A total of 156 patients who met the inclusion criteria were finally enrolled in this study.
One hundred and nine children were randomly assigned to the training set and 47 children were assigned in the validation set. There were no significant differences between the two sets in clinical characteristics and surgical reduction. Surgical reduction was performed in 64 patients in the training set and 23 patients in the validated sets (Table 1).

Development of the score

The univariate analysis using the training set showed that the duration of symptoms (p= 0.046), the mental state (p= 0.000), palpable abdominal mass (p=0.021), bloody stools (p= 0.033), elevated white blood cells (p=0.029), intra peritoneal effusion in ultrasound (p=0.007) and the length of the mass (p=0.005) were significantly associated with surgical treatment of intussusception. The significant factors were selected for the multivariate analysis.
After multivariate analysis, bloody stools (p =0.033; OR=2.61), the duration of symptoms (p= 0.028, OR= 1.02), the length of the intussusception (p=0.014; OR= 1.265) were independent predictors of surgical treatment (Table 2) were identified as independent risk factors of surgery.
A model that incorporated these independent factors was developed using the ''KNIME'' platform. Only three factors were considered in the final model which were bloody stools, duration of symptoms, and the length of the intussusception.
The SVM classifier was trained on the training set after pre-processing. The model's performance was evaluated on the test set using a range of classification metrics. The SVM model demonstrated a sensibility of 95 % and specificity of 95%. In addition to SVM, logistic regression was employed for comparative analysis. The logistic regression model was trained and evaluated following the same procedures as SVM. The results obtained from the logistic regression model were sensibility of 87% and specificity of 87%. The AUROC value of our model for predicting surgical treatment was 0.7373 (Figure 1).

Table 1. Patients and operative characteristics

Variables	Training set (n=109)	Validation set (n= 47)	p-value
Surgical reduction, n (%)	64 (58.7%)	23(48.9%)	0.259
Age (months), n (%)			0.855
<24months	82 (75.2)	36 (76.6)	
>=24months	27 (24.8)	11 (23.4)	
Gender			0.059
Male	54 (49.5)	31(66)	
Female	55 (50.5)	16 (34)	
Weight (Kg), mean±SD	11.3±5.5	11.8 ±5.1	0.583
History of infection, n (%)			0.148
Yes	22 (20.2)	5(10.6)	
No	87(89.8)	42(89.4)	
Duration of symptoms (h), mean±SD	40(43)	34(29)	0.406
Vomiting, n (%)			0.601
Yes	89 (81.7)	40 (85.1)	
No	20 (18.3)	7 (14.9)	
Abdominal pain (paroxistic crying), n (%)			0.983
Yes	81 (74.3)	35 (74.5)	
No	28 (25.7)	12 (25.5)	
Bloody stools, n (%)			0.978
Yes	42(38.5)	18(38.3)	
No	67 (61.5)	29(61.7)	
Abdominal mass, n (%)			0.379
Yes	21 (19.3)	12 (25.5)	
No	88 (80.7)	35 (74.5)	
Temperature, mean	37.38(0.51)	37.29 (0.49)	0.418
White Blood Cells (WBCs),*10⁹/l, median (SD)	12555(3970)	12288(3171)	0.65
C-reaction protein ²(CRP), mg/L, median (range)	14.60(16.21)	12.42 (18.55)	0.46
Kalium(K), mmol/L, mean±SD	3.8(0.41)	3.7(0.39)	0.62
Sodium(N), mmol/L, mean±SD	136.3(2.42)	135.9(2.46)	0.34
Chloride (CL), mmol/L, mean±SD	100.26 (3.16)	100.74 (3.60)	0.39
Long axis diameter in Ultrasound, mean (cm)	5.46(2.74)	5.06(2.52)	0.684
Enlarged lymph node in ultrasound, n (%)			0.986
Yes	79 (72.5)	34 (72.3)	
No	30 (27.5)	13 (27.7)	
decrease of the blood flow within the intussusception in ultrasound, n (%)			0.370
Yes	9 (8.3)	2 (4.3)	
No	100 (91.7)	45 (95.7)	
Mental state			0.938
Good	91 (83.5)	39 (83.0)	
Poor	18 (16.5)	8 (17)	
Season			0.48
Winter/ Automns	46 (42.2%)	17(36.2%)	
Summer/spring	63(57.8%)	30(63.8%)	

SD : Standard Deviation

Table 2. Univariate and multivariate analysis of the predictors of surgical intervention

	Univariate analysis		Multivariate analysis	
	OR[1] (95% CI)	P	OR (95% CI)	P
The gender	0.706 (0.328;1.518)	0.372		
Age more than 24 months		0.062		
Weight (kg)		0.144		
Duration of symptoms (h)	16.872(0.324;33.419)	**0.046**	1,02(1,002;1,039)	**0.028**
Season	1.001(0.463;2.167)	0.997		
Vomiting	1.067(0.397;2.869)	0.897		
Fever	6.150 (1.958;19.319)	**0.001**		
Poor mental state	0.505 (0.413;0,619)	**0.000**		
Palpable abdomial mass	0.270(0.084;0.866)	**0.021**		
Bloody stool	0.412(0.181;0.939)	**0.033**	2.61(1.08;6.33)	**0.033**
White Blood Cells(WBCs), *10⁹/l, median(SD[2])		**0.029**		
Hemoglobin (g/dl)		0.773		
C-reaction protein [2](CRP), mg/L, median (range)		0.247		
Kalium(K), mmol/L, mean±SD		0.166		
Sodium(N), mmol/L, mean±SD		0.158		
Chloride (CL), mmol/L, mean±SD		0.092		
Intraperitoneal Effusion	0.338(0.152;0.749)	**0.007**		
Length of the mass		0.005	1,265(1,049;1,524)	**0.014**
Decrease of blood perfusion	0.159(0.019;1.32)	0.055		
Enlarged lymh node	0.512(0.209;1.256)	0.140		

1: OR (95% CI): Odds Ratio with a 95% Confidence Interval; **2**: SD : Standard Deviation

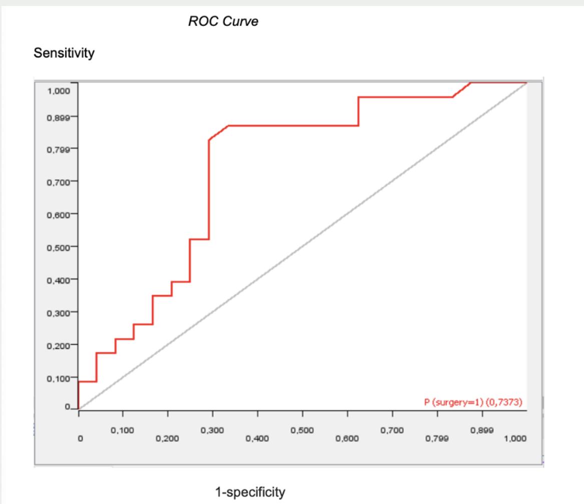

Figure 2. AUROC of surgical prediction

Discussion

In this study, a machine learning model was employed to develop and validate a predictive model for surgical intervention in patients with ileocolic intussusception. The clinic-pathologic risk factors incorporated into this model included bloody stools, the duration of symptoms, and the length of the intussusception. The SVM (Support Vector Machine) model exhibited a sensitivity of 95% and a specificity of 95%, while the logistic regression model showed a sensitivity of 87% and a specificity of 87%.

Few studies have focused on the development of intelligent models to predict surgical management using machine learning models in pediatric pathologies [12,14 ,15]. Ting et al. [16] developed a nomogram to predict pathological intussusception before surgical intervention in children using only logistic regression. Guo et al. [8] developed a model to predict recurrent cases of intussusception. They utilized three parallel models: Extreme Gradient Boosting (XGBoost), Logistic Regression, and Support Vector Machine (SVM). They found that machine learning models could effectively predict recurrent cases of intussusception in children.

In the present study, we aimed to predict surgical intervention using SVM. The variables collected for the univariate analysis were age, gender, weight, the duration of symptoms, the season, the presence of vomiting, the presence of fever, the mental state, bloody stools, ultrasonographic parameters (length of the mass, the decrease of blood perfusion, the presence of intra peritoneum effusion, the presence of enlarged lymph nodes), and biologic parameters (the white cells value, the C-reactive protein, the serum kalium, the serum sodium, and serum chloride). The bloody stools, the duration of symptoms and the length of the intussusception were independent risk factors for surgery. The model that incorporated these potential predictors was validated using the validation set with ‘’Scorer’’ in the Knime platform.

The long duration of symptoms was related to the loss of intestinal viability in case of intussusception. Thus, several studies found that the duration of symptoms was a risk factor for failure of hydrostatic reduction. The cut off value was mostly 48 or 72 hours as found in our study [17, 18]. Zhuang et al found a cut-off value of 24 hours and explained this difference by the duration of symptoms less than 48 hours in most enrolled cases.

Bloody stools are one of the classic triads of intussusception. It’s a poor predictor of intestinal viability, however, it has been reported as a predictor of failure of hydrostatic reduction [18, 19]. In the present study, it was also demonstrated as an independent predictor for surgery after logistic regression.

Previous studies reported that the length of the intussusception was significantly longer in pathological intussusceptions than in primary intussusceptions [16, 20]. Due to the presence of PLPs, the proximal retracted small bowel carries the mesentery into the distal bowel tract, so pathological intussusceptions would involve a longer length of bowel. This may explain the significant association between the long axis diameter of the intussusception and the surgical intervention such as found after logistic regression in our study. The longer diameter was prone to a higher risk of surgical intervention in our predicting model. Other poor prognosis signs in ultrasounds such as the decrease or the absence of the blood flow within the intussusception, the presence of enlarged lymph nodes and intra peritoneum effusion were found associated with a poor hydrostatic reduction risk [2, 3,18]. In our study, the presence of intraperitoneal effusion was a factor associated with surgery in univariate analysis but wasn't an independent factor after the multivariate analysis. The rejection of these factors after logistic regression may be the result of the elimination of confounding factors.

The presence of fever as well as the increase in WBCs counts were associated with intestinal necrosis in previous studies. Chen et al [21] reported that patients who underwent intestinal resection due to intestinal necrosis had significantly higher WBCs count than those without any resection. That's why we included fever and WBCs in the studied variables. We found that they were associated with surgical resection in univariate analysis but after the logistic regression weren't independent risk factors. Our results were consistent with previous studies [3]. Thus, these factors were not incorporated into our model.

Somnolence, listlessness, and the pale face are clinical elements that reflect a poor mental state. In our study, poor mental state did not predict a greater chance of reduction failure. Zhuang et al [2] found that mental state was a risk factor for surgical intervention and incorporated it in a nomogram predicting surgical treatment in children. However, they explained a poor mental state by dehydration caused by vomiting. This may be a confounding factor. In our study, serum electrolytes (serum sodium, serum chloride and serum kalium) as well as the ascension of C-reactive protein were not significantly associated with surgical intervention. These results were consistent with previous studies [2,3].

It's known that the incidence of intussusception caused by a pathological lead point (PLP) increases with age from 5% in the first year of life to 60% in 5 to 14 years old [1, 22]. In this study, we included children aged less than 3 years with ileocolic intussusception. We found that age was associated with surgical intervention however it was not an independent factor of failure of non-operative treatment after logistic regression. In some previous studies, an age of more than two years was identified as an independent predictor for surgery [23, 24]. This may be given that the incidence of pathological intussusceptions was probably comparable between the cohorts of patients less than 2 years and patients aged more than two years old (less than three years) in our study. However, other studies included patients aged less than seven years where the incidence of PLP increases and then the age may be found as an independent factor of surgery. Zhuang et al [2] didn't identify a cut-off value of age as an independent factor of hydrostatic reduction failure like in our study and they explained this by the difference in the data set like the inclusion criteria of a more aged population.

Other factors such as gender, weight, the season, and the presence of vomiting were found as independent factors of surgery [2, 3, 18]. The rejection of these factors in the model may be due to the nuances in the data set and the cut-off values which are different from one study to another. After the model was constructed, we validated it using the validation set. The sensitivity and specificity of this model using 'Scorer' were high (95% and 95% respectively in SVM), with an AUROC value of 0.7373 The knowledge of three parameters which are the presence of bloody stools, the duration of symptoms and the length of the intussusception may facilitate and orientate therapeutic decisions.

The limits of this study were its retrospective character and the single center database. Differences were found with previous studies which may be explained by differences in the inclusion criteria. The prediction of the adequate therapeutic method for every patient might help the physician to communicate with the parents about the importance of attempting a nonoperative reduction and the prognosis of the child. Larger prospective multicenter studies with similar inclusion criteria are needed to validate the model.

Conclusion

This SVM-based model, using three specific clinical parameters (bloody stools, duration of symptoms, and the length of intussusception) demonstrated high predictive accuracy with sensitivity and specificity values of 95%. It provides valuable insights for predicting the need for surgical intervention in pediatric intussusception cases. Knowledge of these parameters may help clinicians in making informed therapeutic decisions. Further validation through larger prospective multicentre studies with similar inclusion criteria is necessary to enhance the model's reliability and applicability.

References

1. Tiwari C, Shah H, Sandlas G, Bothra J. Paediatric Intussusception: A Clinical Scoring System to Predict the Risk of Operative Intervention. J Mother Child 2020;24(1):19-23.
2. Zhuang Y, Wang X, Fan X, Li F, He G, Luo M et al . Developing a nomogram for predicting surgical intervention in pediatric intussusception after hydrostatic reduction. Front Pediatr 2023;11:1092548.
3. Khorana J, singhavejsakul J, Ukarapol N, laohapensang M, Jakraphan Siriwongmongkol J,1 and Patumanond J. Pronostic indicators for failed nonsurgical reduction of of intussusception. Therapeutics and Clinical Risk Management 2016;12
4. Carroll AG, Kavanagh RG, Ni Caoilfhionn, Cullinan NM, Lavelle LP and Malone DP . Comparative Effectiveness of Imaging Modalities for the Diagnosis and Treatment of Intussusception: A Critically Appraised Topic. Acad Radiol 2017; 24(5):521-529
5. Kelley-Quon LI, Arthur LG, Williams RF, Goldin AB, St Peter SD, Beres AL et al. Management of Intussusception in Children: A Systematic Review. J Ped Surg 2021; 56(3):586-596
6. Khorana J, Singhavejsakul J, Ukarapol N, Laohapensang M, Wakhanrittee J and Patumanond J. Enema reduction of intussusception: the success rate of hydrostatic and pneumatic reduction. Ther Clin Risk Manag. 2015;11:1837–42.

7. Bekdash B, Marven SS and Sprigg A. Reduction of intussusception: defining a better index of successful non-operative treatment. Pediatr Radiol 2013;43(6):649–956.
8. Guo, Jy., Qian, Yf. Predicting recurrent cases of intussusception in children after air enema reduction with machine learning models. Pediatr Surg Int 2023;39, 9
9. Khorana J, Singhavejsakul J, Ukarapol N, Laohapensang M, Siriwongmongkol J and Patumanond J. Prognostic indicators for failed nonsurgical reduction of intussusception. Ther Clin Risk Manag 2016; 12:1231–7.
10. Wu TH, Huang GS, Wu CT, Lai JY, Chen CC and Hu MH . Clinical characteristics of pediatric intussusception and predictors of bowel resection in affected patients. Front Surg 2022; 9:926089.
11. He N, Zhang S, Ye X, Zhu X, Zhao Z and Sui X. Risk factors associated with failed sonographically guided saline hydrostatic intussusception reduction in children. J Ultrasound Med 2014; 33(9):1669–75.
12. Bianco A, Al-Azzawi ZAM, Guadagno E, Osmanlliu E, Gravel J and Poenaru D. Use of machine learning in pediatric surgical clinical prediction tools: A systematic review. J Ped Surg 2023; 58: 908e916
13. Atema J, Van Rossem C, Leeuwenburgh M, Stoker J and Boermeester MA. Scoring system to distinguish uncomplicated from complicated acute appendicitis. B J Surg 2015; 102(8):979–990
14. Hu Y, Gong X, Shu L, Duan H, Luo Q, Zhang B et al. Understanding risk factors for postoperative mortality in neonates based on explainable machine learning technology. J Ped Surg 2021; 2165-2171
15. Zeng X, Hu Y, Shu L, Li J, Duan H, Shu Q et al. Explainable machine-learning predictions for complications after pediatric congenital heart surgery.Scientific Reports 2021; 11.
16. Ting X, Xufei D, Jiangbin L, Weijue Xu, Zhibao Lv and Guogang Ye. Development and Validation of a Nomogram for Predicting Pathological Intussusceptions in Children Prior to Surgical Intervention. Front in Pediatr 2022;10:877358.
17. Rejenin JA, Festen C, Van Roosmalen RP. Intussception. Factors related to treatment. Arch Dis Child1990.65(8):871-3.
18. Khorana J, Patmanond J, Ukarapol, Laohapensang M, Visrutaratna P, Singhavejsakul J. Clinical prediction rules for failed non operative reduction of intusception. Therapeutics and clinical risk management 2016 :12 1411-1416
19. He N, Zhang S, Ye X et al. Risk factors associated with failed sonographically guided saline hydrostatic intussusception reduction in children. J Ultrasound Med 2014;33(9):1669–75.
20. Zhang Y, Dong Q, Li SX, Zhu X, Zhao Z and Sui X. Clinical and ultrasonographic features of secondary intussusception in children. Eur Radiol 2016; 26:4329–38.
21. Chen B, Cao J, Yan C, Zheng C, Chen J and Guo C. A promising new predictive factor for detecting bowel resection in childhood intussusception: the lymphocyte- C-reactive protein ratio. BMC Pediatr 2021;21(1):577.
22. Young DG. O'Neil JA, Jr, Rowe MI, Grosfeld JL, Grosfeld JL, Fonkalsrud EW and Coran AG. Intussusception. Pediatric surgery 1998: 1185–1198.pp. 1981 ISBN: 978-0815165187
23. Khorana J, Singhavejsakul J, Ukarapol N, Laohapensang M, Siriwongmongkol J and Patumanond J. Prognostic indicators for failed nonsurgical reduction of intussusception. Ther Clin Risk Manag 2016; 12:1231–7.
24. Khorana J, Patumanond J, Ukarapol N, Laohapensang M, Visrutaratna P and Singhavejsakul J. Clinical prediction rules for failed nonoperative reduction of intussusception. Ther Clin Risk Manag 2016; 12:1