Research Paper

Development and Deployment of Web Application Using Machine Learning for Predicting Intraoperative Transfusions in Neurosurgical Operations

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ABSTRACT

Background and Aim: Preoperative blood product preparation is a common practice in neurosurgical patients. However, over-requesting of blood is common and leads to the wastage of blood bank resources. Machine learning (ML) is currently one of the novel computational data analysis methods for assisting neurosurgeons in their decision-making process. The objective of the present study was to use machine learning to predict intraoperative packed red cell transfusion. Additionally, a secondary objective focused on estimating the effectiveness of blood utilization in neurosurgical operations.

Methods and Materials/Patients: This was a retrospective cohort study of 3021 patients who had previously undergone neurosurgical operations. Data from the total cohort were randomly divided into a training dataset (n=2115) and a testing dataset (n=906). The supervised ML models of various algorithms were trained and tested with test data using both classification and regression algorithms.

Results: Almost all neurosurgical conditions had a cross-match to transfusion ratio of more than 2.5. Support vector machine (SVM) with linear kernel, SVM radial kernel, and random forest(RF) classification had a performance with good AUC of 0.83, 0.82, and 0.82, respectively, while RF regression had the lowest root mean squared error and mean absolute error.

Conclusion: In almost all neurosurgical surgeries, preoperative overpreparation of blood products was detected. The ML algorithm was proposed as a high-performance method for optimizing blood preparation and intraoperative consumption. Furthermore, ML has the potential to be incorporated into clinical practice as a calculator for the optimal cross-match to transfusion ratio.

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Highlights

• In the practice of neurosurgery, excessive blood product preparation for operations was seen.

• Machine learning (ML) is one of the innovative computer data analysis approaches used to assist neurosurgeons with preoperative blood product preparation.

• ML algorithms were suggested as a high-performance way to optimize the preparation of blood and its use during surgery.

Plain Language Summary

Preparing blood products before surgery is common in neurosurgical patients but wastage of blood resources is also important because of too many requests. Therefore, machine learning (ML) has been introduced as a new computational data analysis to help neurosurgeons in decision-making. The extracted algorithms optimize the preparation of blood products before and during the operation. In this retrospective cohort study, the data of 3,021 patients who had previously undergone neurosurgical operations were randomly divided into training and testing datasets. Almost all neurosurgical conditions had a cross-match to more than 2.5 transfusion ratio. ML algorithms can optimize the preparation of blood products before surgery and their consumption during surgical procedures.

1. Introduction

Preoperative blood product preparation is a routine practice in neurosurgical operations because several procedures are at high risk of intraoperative transfusion. [1-3] Traumatic brain injury (TBI) has an increased risk of transfusion by 36%, while 25% of ruptured aneurysms have a risk of transfusion. Moreover, the transfusion rate of neurosurgical operations in children has been reported to be between 25-95% of cases [2-5]. However, the cross-match to transfusion (C/T) ratio has been revealed at a high level because neurosurgeons usually request more units of preoperative blood products for safety in cases of unexpected bleeding [6, 7]. From the literature review, preoperative over-ordering of blood product preparation has been reported. Chotisukarat et al. demonstrated the C/T ratio in 1,018 patients with elective neurosurgical procedures was 4.3% [6]. Furthermore, Saringcarinkul et al. studied preoperative blood product preparation and intraoperative transfusion and found that the C/T ratio was high at 6.6 [7].

In the era of the Coronavirus (COVID-19) pandemic, blood donation has been disrupted globally to a significantly lower level than normal period [8]. Chandler et al. reported that based on a survey approximately half of the blood donations decreased during the COVID-19 pandemic in European countries, and a remarkable drop was also observed in 32 African countries as well [9]. Therefore, optimization between preoperative blood production and intraoperative transfusion should be considered in case of a pandemic situation.

Machine learning (ML) is a novel computer data analysis technology that has been used to assist physicians in making decisions in a variety of domains, including diagnosis, therapy response prediction, and prognostication [10]. For blood transfusion prediction, Liu et al. studied the predictability of several ML algorithms in patients who received mitral valve surgery and found that the CatBoost algorithm established the best prediction with an area under the curve (AUC) of 0.888 (95% CI (confidence interval): 0.845-0.909) [11], while Huang et al. reported that the model for the extreme gradient boosting and random forest (RF) algorithms had high accuracy at 83.34 and 82.35, respectively [12]. Moreover, Feng et al. determined the predictability of ML in patients who received surgery and found that the best-supervised ML algorithm for the prediction of transfusion was a light gradient boosting machine with AUC 0.908 (95% CI 0.907-0.913) [13]. From a literature review, few studies have mentioned ML applications for predicting blood transfusion needs in neurosurgical operations. Therefore, the present study aimed at using ML to predict intraoperative packed red cell transfusion. Besides, the secondary objective was to estimate the effectiveness of blood utilization in neurosurgical operations.

2. Materials and Methods

Study design and study population

The retrospective cohort study was initiated by searching the electronics-based medical records of patients who were admitted and operated on in Songklanagarind Hospital, southern Thailand between January 2014 and January 2019. Patients with unavailable details of cross-match and transfusion were excluded. Collected data included age, gender, underlying disease, neurosurgical condition, height, body weight, American society of anesthesiologists (ASA) classification, operation, preoperative hematological laboratories, estimated blood loss by physicians, and units of intraoperative packed red cell transfusion.

Various neurosurgical conditions were categorized as follows: cranial tumor, cerebral aneurysm, traumatic brain injury, cerebrovascular disease, spinal conditions, congenital disease, infection, and normal pressure hydrocephalus. In detail, spinal conditions were classified according to etiology, such as tumor, trauma, infection, and degeneration. Moreover, congenital diseases were grouped into brain congenital diseases (congenital hydrocephalus) and spinal brain congenital diseases (spinal dysraphism). Patients' physical status was evaluated using the ASA classification, and an emergency surgical procedure was defined as a delayed operation, possibly leading to a significant rise in the risk of life, disabilities, or injuries [14].

The primary outcomes of the present study were the event of intraoperative packed red cell transfusion for each patient as the binary categorical variable, and the number of units of packed red cell transfusion as the continuous variable. Therefore, the secondary outcome described the effectiveness of blood utilization in general practice via the C/T ratio, transfusion probability (TP), and transfusion index (TI). These indexes were defined according to Zewdie et al. In detail, a C/T ratio of 2.5 or less indicated the effectiveness of blood utilization. Moreover, TP of 30% or more and TI of 0.5 or more revealed effective blood usage [15].

Ethical considerations

The present study was approved by the Human Research Ethics Committee, Faculty of Medicine, Prince of Songkla University (REC No. 64-477-10-1). Because of the retrospective design of the study, informed consent could not be obtained from the patients. Therefore, an informed consent waiver statement and the approval of the ethics committee at Prince of Songkla University waived the need for informed consent. All methods were performed following the relevant guidelines and regulations, adhering to the Strengthening the Reporting of Observational Studies in Epidemiology guidelines. The patient's identification numbers were encoded before analysis.

Statistical analysis

We calculated the sample size using receiver operating characteristics (ROC) with the AUC formula [16]. Based on an AUC of 0.908 from the study of Feng et al. [13], a minimum of 540 patients from the testing data would be required to estimate the performance of the predictive model with a given marginal error of 0.03 and a 95% confidence level.

The clinical characteristics were described using proportion and percent, while descriptions of the continuous variables were performed by Mean±SD and standard deviation. The chi-square test was used to estimate the difference in the proportions between the two groups, whereas the independent t-test was performed for comparing means between the transfusion group and the non-transfusion group. A P-value <0.05 was considered statistically significant. Subsequently, the significant variables were included to train by ML in the next procedure.

Machine learning

The various algorithms for supervised ML were performed with two proposed approaches as follows: ML classification and ML regression. ML classification was performed for predicting the binary output that was labeled as transfusion or non-transfusion. The algorithms for classification were conducted as follows: Naïve Bayes (NB) support vector machine with the linear kernel (SVML), support vector machine with the radial kernel (SVMR), k-Nearest Neighbors (KNN), Decision tree (DT), random forest (RF), and artificial neural network (ANN). Using ML regression, the number of units for red cell transfusion was predicted and calculated as a continuous quantity output. KNN, DT, RF, and ANN were performed as a response to this problem.

The training dataset and testing dataset were established from the 70/30 splitting procedure. The training dataset was performed with five-fold cross-validation, and the training model for each algorithm was built. Therefore, the performance of these models was estimated with the testing dataset. The performance of each algorithm was calculated for sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy from the confusion matrix. Further, the ROC with AUC was estimated for ML classification, with an AUC of ≥0.8 indicating good performance [17, 18].

For regression performance, we used the scatter plot for comparing true values and predicted numbers of units for red cell transfusion. Pearson's correlation, Spearman's rank correlation, R-squared (R^2), root mean squared error (RMSE) and mean absolute error (MAE) were used to estimate those results. Machine learning was performed using the R program, version 4.0.3 (The R project) with the "caret" package. Hence, the best training model was developed and deployed as a web application using the "shiny" package.

3. Results

Clinical and radiological characteristics

A total of 3,122 patients' medical records were reviewed, with 101 patients being excluded due to unavailable outcomes. Consequently, the remaining 3,021 patients were randomly divided into 70% training dataset and 30% testing dataset. Baseline clinical characteristics are shown in Table 1. The population showed a slight male predomination, and the Mean±SD age was 46.36±20.71 years. Patients with intraoperative transfusions had a significantly higher mean age than the non-transfusion group. Brain tumor (45.7%) was a major neurosurgical disease in the present cohort, while the three most common operations were craniotomy (36.1%), craniectomy (12.1%), and burr hole (8.7%), respectively. For the transfusion group, an emergency operation was performed in more than half. Moreover, patients who received intraoperative packed red cell transfusions had a history of more frequent warfarin usage than the non-transfusion group.

Table 2 shows several preoperative laboratories and other continuous variables. Patients with transfusions had anemia and lower platelet counts than other groups, while white blood cell count and neutrophil-to-lymphocyte (N/L) ratio increased in the transfusion group. Furthermore, the partial prothrombin time (PTT) ratio and international normalized ratio (INR) of the transfusion group were prolonged compared with the control group.

Effectiveness index of preoperative blood preparation

The C/T ratio, TP, and TI in the present study are shown in Table 3. A high C/T ratio was observed in the total cohort. Almost all neurosurgical conditions had a C/T ratio of higher than 2.5, except TBI, while an extremely high C/T ratio was observed in spinal congenital diseases such as lipomyelomeningocele. In operation, only decompressive craniectomy had a low C/T ratio, whereas the remaining procedures had a high index. Moreover, shunt operation, ventriculostomy, and burr hole had a very high index.

Factors associated with intraoperative transfusion

Increased age was significantly associated with transfusion (odds ratio (OR) 1.5, 95%CI 1.2-1.9). Other clinical characteristics that increased the risk of intraoperative transfusion were female gender, diabetes mellitus, renal failure, chronic warfarin usage, increased ASA classification, and increased amount of estimated blood loss. Neurosurgical conditions increased transfusion risk. In detail, when the reference group involved patients with brain tumors, patients with TBI (OR 1.70, 95%, CI 1.36-2.07) and cerebral aneurysm (OR 1.60, 95%CI 1.32-2.06) had a significantly higher risk for intraoperative blood utilization than the compared group. Based on the operation, decompressive craniectomy increased the risk of transfusion compared with craniotomy (OR 1.60, 95% CI 1.12-2.03). Furthermore, an emergency operation was a positive risk of intraoperative transfusion, whereas the operation of surgical site infection was the protective factor. For preoperative laboratories, the risk factors associated with blood transfusion were white blood cell count, N/L ratio, prolonged PTT ratio, and INR, while the level of hemoglobin, hematocrit, and platelet were protective factors for intraoperative transfusion, as shown in Figure 1.

Machine learning

The total dataset was randomly split into a training dataset (n=2115) and a testing dataset (n=906). Using the training dataset, various algorithms of supervised ML classification were used to build the predictive model with factors associated with intraoperative transfusion in the former step. In detail, the model of each algorithm was turned and optimized for the best parameters using the caret package with five-fold cross-validation. As a result, SVML, SVMR, DT, and RF had AUCs at a good level, as shown in Figure 2, whereas the models for SVML, SVMR, and RF had high sensitivity, PPV, and accuracy, as shown in Table 4.

Using ML regression algorithms, the number of units of the packed red cell was predicted. The model of RF algorithms had the lowest values of RMSE and MAE. The actual unit of the transfused packed red cells and predicted units are plotted in Figure 3. Therefore, the results of the RF model had the highest correlation with the true values. For implications in general practice, we proposed the example of the web application via https://psuneurosx.shinyapps.io/RF_Transfusion/, as shown in Figure 4.

Table 1. Demographic data by red cell transfusion (n=3021)

Characteristics		No. (%)			P*
		Total	Intraoperative Red Cell Transfusion		
			No (n=1779)	Yes (n=1242)	
Sex	Male	1567(51.9)	991(55.7)	576(46.4)	<0.001
	Female	1454(48.1)	788(44.3)	666(53.6)	
Age (y)	0-15	323(10.7)	216(12.1)	107(8.6)	0.002
	>15-60	1921(63.6)	1132(63.6)	789(63.5)	
	>60	777(25.7)	431(24.2)	346(27.9)	
Underlying disease	Hypertension	916(30.3)	535(30.1)	381(30.7)	0.72
	Diabetes mellitus	344(11.4)	184(10.3)	160(12.9)	0.03
	Dyslipidemia	444(14.7)	277(15.6)	167(13.4)	0.10
	Liver disease	101(3.3)	55(3.1)	46(3.7)	0.35
	Renal failure	142(4.7)	71(4.0)	71(5.7)	0.02
Preoperative current medication	Antiplatelet	117(3.9)	62(3.5)	55(4.4)	0.18
	Clexane	12(0.4)	8(0.4)	4(0.3)	0.58
	Warfarin	27(0.9)	10(0.6)	17(1.4)	0.02
Neurosurgical condition	Cranial tumor	1382(45.7)	836(47.0)	546(44.0)	<0.001
	Cerebral aneurysm	412(13.6)	198(11.1)	214(17.2)	
	Traumatic brain injury	466(15.4)	222(12.5)	244(19.6)	
	Non-aneurysm cerebro-vascular disease	267(8.8)	155(8.7)	112(9.0)	
	Spinal operation-tumor	155(5.1)	118(6.6)	37(3.0)	
	Spinal operation-trauma	111(3.7)	76(4.3)	35(2.8)	
	Spinal operation-degenerative disease	34(1.1)	28(1.6)	6(0.5)	
	Spinal operation-infection	10(0.3)	3(0.2)	7(0.6)	
	Congenital disease–brain	71(2.4)	58(3.3)	13(1.0)	
	Congenital disease–spine	28(0.9)	21(1.2)	7(0.6)	
	Infection(non-surgical site infection)	76(2.5)	55(3.1)	21(1.7)	
	Normal pressure hydro-cephalus	9(0.3)	9(0.5)	0(0)	
American society of anesthesiologists classification	1	2(0.1)	2(0.1)	0	<0.001
	2	215(7.1)	152(8.5)	63(5.1)	
	3	2764(91.5)	1611(90.6)	1153(92.8)	
	4	40(1.3)	14(0.8)	26(2.1)	

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Characteristics		No. (%)			P*
		Total	Intraoperative Red Cell Transfusion		
			No (n=1779)	Yes (n=1242)	
Neurosurgical operation	Craniotomy	1090(36.1)	442(24.8)	648(52.2)	<0.001
	Craniectomy	365(12.1)	110(6.2)	255(20.5)	
	Suboccipital or, rectosigmoid approach	178(5.9)	90(5.1)	88(7.1)	
	Endoscopic approach with tumor removal	144(4.8)	111(6.2)	33(2.7)	
	Cranioplasty	38(1.3)	28(1.6)	10(0.8)	
	Burr hole with biopsy/aspiration/irrigation	262(8.7)	224(12.6)	38(3.1)	
	Spinal operation with instrumentation	170(5.6)	112(6.3)	58(4.7)	
	Spinal operation without instrumentation	137(4.5)	110(6.2)	27(2.2)	
	Spinal operation in congenital condition	25(0.8)	17(1.0)	8(0.6)	
	Ventriculostomy insertion	157(5.2)	136(7.6)	21(1.7)	
	Shunt insertion	252(8.3)	232(13.0)	20(1.6)	
	Other	203(6.7)	167(9.4)	36(2.9)	
	Emergency operation	1439(47.6)	764(42.9)	675(54.3)	<0.001
	Surgical site operation	93(3.1)	71(4.0)	22(1.8)	0.001

* P of chi-square test

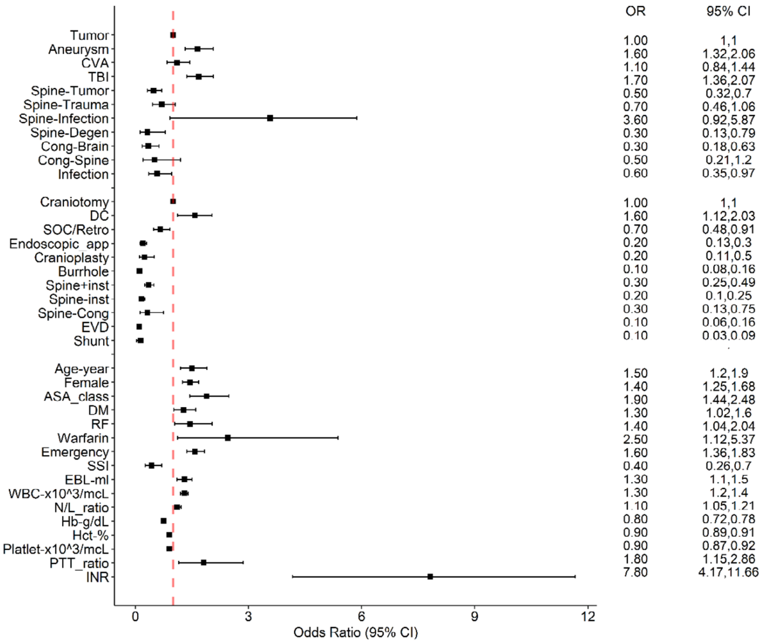

Figure 1. The odds ratio of variables associated with intraoperative transfusion

Table 2. Comparison of preoperative laboratory and other variables by red cell transfusion (n=3021)

Variables	Mean±SD	No. (%) Intraoperative Red Cell Transfusion		P*
		No	Yes	
Hematocrit (%)	37.99±11.11	13.16(5.64)	35.93(7.07)	<0.001
Hemoglobin (g/dL)	12.68±4.90	13.16(5.64)	11.99 3.44)	<0.001
White blood cell count (x10³/µL)	11.44±9.45	10.90(4.94)	12.22(13.46)	0.001
Neutrophil (%)	68.32±16.89	67.78(15.52)	69.10(18.65)	0.04
Lymphocyte (%)	22.91±13.93	23.42(13.52)	22.17(14.40)	0.01
Neutrophil-to-lymphocyte ratio	6.25±9.80	5.73(8.67)	7.00(11.28)	0.001
Platelet count (x10³/µL)	295.06±119.00	301.09(116.63)	286.41(121.83)	<0.001
Prothrombin time ratio	0.96±0.16	0.95(0.13)	0.97(0.19)	0.01
International normalized ratio	1.06±0.16	1.04(0.11)	1.08(0.21)	<0.001
Age (y)	46.36±20.71	45.41(20.88)	47.72(20.39)	0.003
Body mass index (kg/m²)	22.99±4.44	23.06(4.56)	22.88(4.26)	0.27
Estimate blood loss (mL)	598.71±929.4	244.15(289.74)	1106.55(1242.36)	<0.001

*P of t-test

4. Discussion

Almost all neurosurgical procedures had a C/T ratio of greater than 2.5, whereas TBI in the present cohort had a C/T ratio of 2.11 with high TP and TI. Because TBI has been considered a risk of unexpected hemorrhage and acute traumatic coagulopathy (ATC); therefore, cross-match and blood utilization were balanced. These results are in agreement with other prior studies. Boutin et al. conducted a systematic review and meta-analysis. They reported that the transfusion rate of TBI was 28.2% (95% CI 27.2% to 29.3%) [3]. Moreover, ATC in TBI was observed at 35.2% (95% CI 29.0-41.4) and an increased transfusion rate was 41% according to Epstein et al. Moreover, chronic warfarin usage and preoperative increased INR, the second-highest impacts to increased risk of transfusion, were in agreement with previous studies [19, 20]. Hence, children were one of the age groups that had been reported to have transfusion risk in the range of 25-95% [1-3]. Conversely, our results were not in agreement with earlier studies that showed the elderly had an increased risk to receive blood transfusion intraoperatively [1, 21]. In the present study, several operations which had high C/T but low TP and TI were less likely to have intraoperative transfusions such as shunt, ventriculostomy, and burr hole procedures. Therefore, the preoperative blood preparation protocol should be discussed and revised to improve the effectiveness of blood utilization.

Currently, several ML algorithms are performed for the prediction of intraoperative packed red cell transfusion for optimizing blood utilization. Huang et al. predicted red cell transfusion in patients with pelvic fracture surgery and reported that an extreme gradient boosting algorithm had the best AUC of 0.99 with 93% sensitivity [12], while Chang et al. found that SVM had an AUC of 0.703-0.707 with 78-79.2% sensitivity for predicting blood transfusion in orthopedic surgery [22]. Moreover, Walczak et al. used the ANN algorithm to predict perioperative transfusion with an AUC of 0.814-0.858 and sensitivity of 75-62% for in-patient operations [23]. As a result, the AUC of SVM and RF algorithms in classification demonstrated good performance with 86%-84% sensitivity. Moreover, the RF with regression algorithm had the lowest RMSEs of 0.99-1.21 in the present study. The concordant findings were similar to what had been shown in previous studies. Feng et al. reported the RMSEs of various regression algorisms with testing data in a range of 0.92-6.26 [13]. As the RF algorithm was achieved with the testing dataset for both classification and regression, we demonstrated that the web application may be a user-friendly tool that could be integrated into general practice.

Table 3. Cross-match to transfusion ratio, transfusion probability, and transfusion index of packed red cells by neurosurgical condition/ operation

	Neurosurgical Condition/ Operation	Preoperative Preparation		Intraoperative Utilization		C/T ratio	TP	TI
		Patient with cross-match (n)	Total cross-match (units)	Patient received transfusion (n)	Total transfusion (units)			
Neurosurgical condition	All	282	10024	1242	3162	3.17	43.10	1.10
	Cranial tumor	1323	4630	546	1412	3.28	41.27	1.07
	Aneurysm	396	1426	214	490	2.91	54.04	1.24
	TBI	448	1584	244	749	2.11	54.46	1.67
	CVA	256	890	112	267	3.33	43.75	1.04
	Spine-tumor	154	537	37	89	6.03	24.03	0.58
	Spine-trauma	108	368	35	66	5.58	32.41	0.61
	Spine-degen	34	109	6	14	7.79	17.65	0.41
	Spine-infection	10	38	7	11	3.45	70.00	1.10
	Cong–brain	55	145	13	20	7.25	23.64	0.36
	Cong-spine	24	71	7	7	10.14	29.17	0.29
	Infection	71	220	21	37	5.95	29.58	0.52
	NPH	3	6	0	0	-	0	0
Neurosurgical operation	Craniotomy	1086	4171	648	1586	2.63	59.67	1.46
	Craniectomy	361	1365	255	820	1.66	70.64	2.27
	SOC/Retro	176	658	88	165	3.99	50.00	0.94
	Endoscopic approach	144	460	33	70	6.57	22.92	0.49
	Cranioplasty	34	101	10	19	5.32	29.41	0.56
	Burr hole	240	741	38	56	13.23	15.83	0.23
	Spinal operation with inst	169	587	58	114	5.15	34.32	0.67
	Spinal operation without inst	134	456	27	76	6.00	20.15	0.57
	Spinal operation in Cong	25	76	8	9	8.44	32.00	0.36
	Ventriculostomy insertion	143	438	21	37	11.84	14.69	0.26
	Shunt insertion	202	515	20	38	13.55	9.90	0.19
	Other	168	456	36	64	7.13	21.43	0.38

Abbreviations: C/T ratio: Cross-match to transfusion ratio; Cong: Congenital disease; CVA: Non-aneurysm cerebrovascular disease; degen: Degenerative disease; inst: Instrumentation; NPH: Normal pressure hydrocephalus; Retro: retrosigmoid approach; SOC: Suboccipital approach; TBI: Traumatic brain injury; TI: transfusion index; TP: Transfusion probability

Table 4. Performances of machine learning each algorithm

Algorithm		Sensitivity	Specificity	PPV	NPV	Accuracy	AUC
Classification	NB	0.78	0.78	0.87	0.65	0.78	0.76
	SVML	0.86	0.79	0.85	0.80	0.83	0.83
	SVMR	0.84	0.79	0.86	0.76	0.82	0.82
	KNN	0.79	0.72	0.81	0.70	0.76	0.76
	DT	0.80	0.84	0.75	0.82	0.77	0.80
	RF	0.84	0.78	0.85	0.78	0.82	0.82
	ANN	0.73	0.80	0.91	0.52	0.75	0.72

Algorithm		Pearson's correlation	P of Pearson's correlation	Spearman's rank correlation	R^2	RMSE	MAE
Regression	KNN	0.75	<0.001	0.62	0.57	1.21	0.77
	DT	0.80	<0.001	0.70	0.63	1.10	0.68
	RF	0.84	<0.001	0.74	0.70	0.99	0.60
	ANN	0.54	<0.001	0.57	0.29	1.52	0.96

Abbreviations: ANN: Artificial neural network; DT: Decision tree; KNN: K-nearest neighbors; NB: Naïve Bayes; SVML: Support vector machine with linear kernel; SVMR: Support vector machine with radial kernel; R^2: R-squared; RF: Random forest classifier; RMSE: Root mean squared error; Mae: Mean absolute error

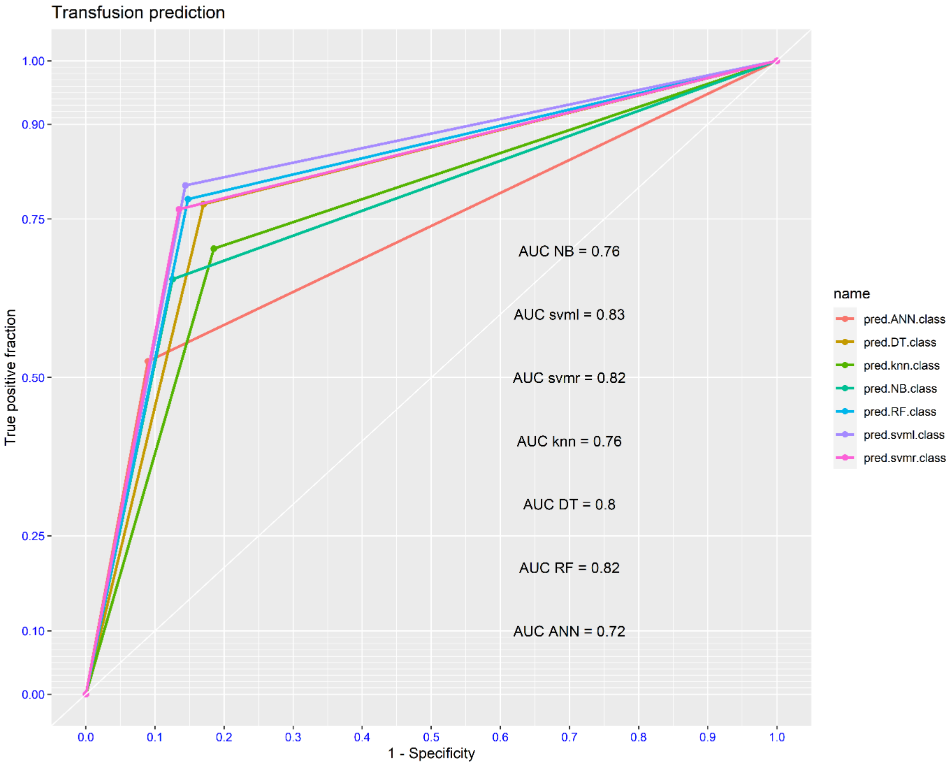

Figure 2. ROC curves of each algorithm

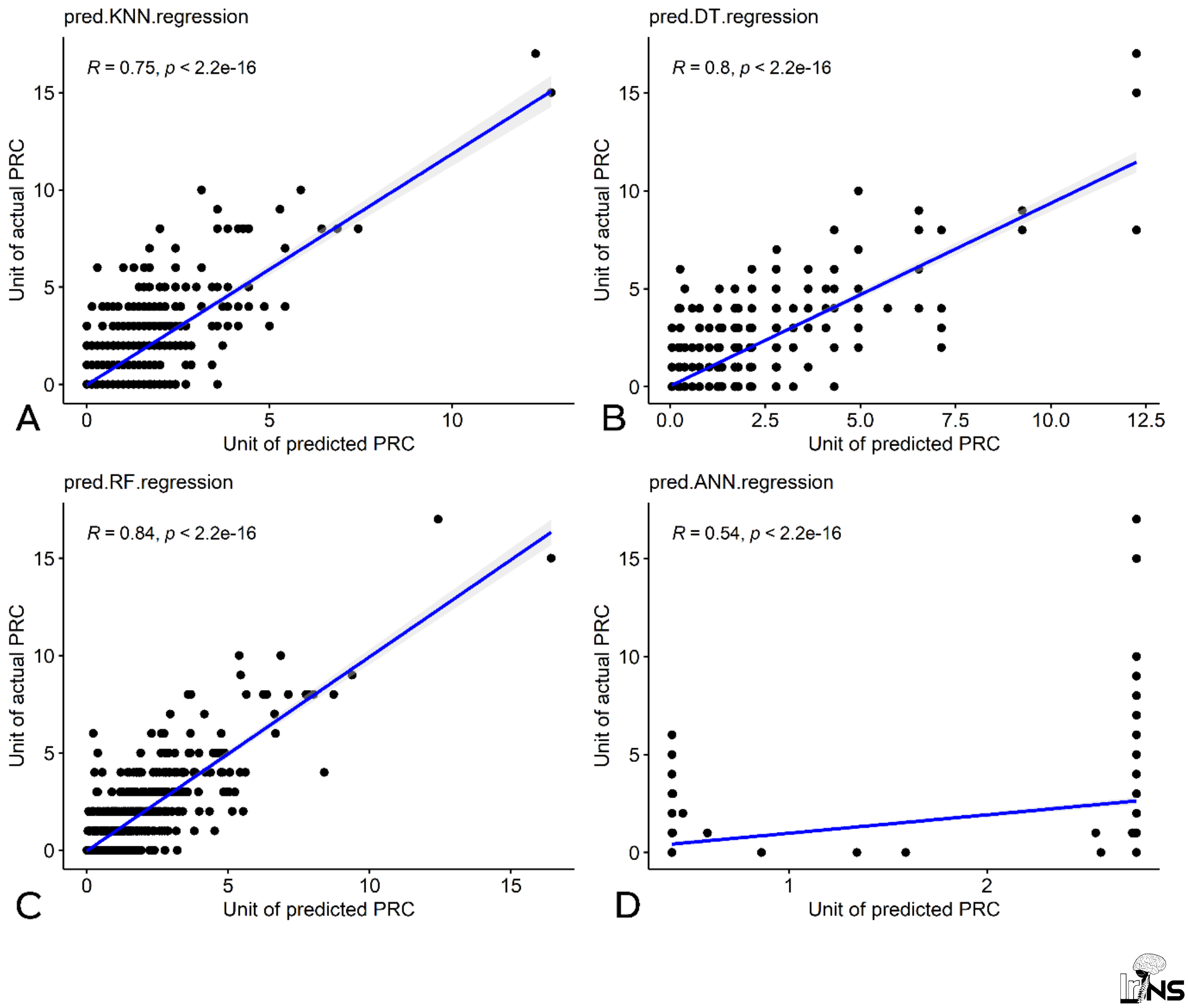

Figure 3. Scatter plot of the actual unit and predicted unit of transfusion. A): K-nearest neighbors B): Decision tree C): Random forest D): Artificial neural network

The ML application for intraoperative transfusion has high sensitivity. These ML models may be involved in general practice as screening tools for supporting neurosurgeons aiming to optimize the Maximum Surgical Blood Order Schedule (MSBOS). To the best of the authors' knowledge, the present study was the 1st paper showing the predictability of ML in intraoperative transfusion, both classification, and regression, in neurosurgical operations. These challenges calculate the MSBOS using ML, while prior studies calculated MSBOS by formula (1.5*TI) [6, 7] or consensus according to the procedures from prior studies [24, 25].

Study limitations

The limitations in the study should be recognized, in which multicollinearity may be considered in several parameters. In detail, we needed to use all significant parameters for the training process because more dimensions in the dataset supported the learning processes and predictability [26]. Therefore, the results demonstrated the high performance of the RF model that was appropriate to deploy as a clinical prediction tool. In the future, external validation and impact analysis studies should be conducted to confirm the performance of the ML model. ML is a modern predictive approach that has been performed in various fields of neurosurgery including for tumors, TBI, or complications [18, 27, 28]. However, another clinical prediction tool has been proposed for predicting clinical outcomes in neurosurgical fields. Nomogram is an alternative approach that has been published as a two-dimensional graphic scoring system [29, 30]. Recently, Tunthanathip et al. compared the performance of the nomogram and ML for the prediction of intracranial injury in children [30]. Hence, a comparison of the capability of MSBOS prediction between both tools should be conducted in the future for balancing blood preparation and utilization in the

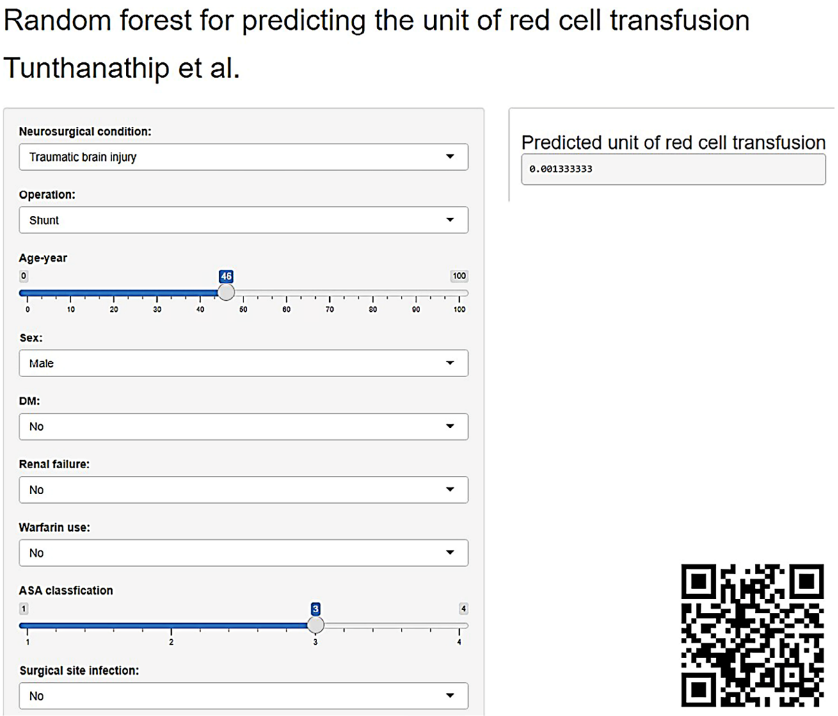

Figure 4. Screenshot of a web application using the random forest algorithm

pandemic era. In addition, the selection bias could be caused by the retrospective study of the present study. Therefore, the prospective multicenter research poses a challenge to carry out in the future for the purpose of evaluating the generalizability of the prediction model.

5. Conclusion

Preoperative overpreparation of blood products was observed in almost all neurosurgical procedures. The ML algorithm was proposed as a high-performance method for optimizing blood preparation and intraoperative consumption. Furthermore, ML has the potential to be incorporated into clinical practice as a calculator for the optimal cross-match to transfusion ratio. However, these results should be interpreted with caution due to the retrospective nature of this study and the possible presence of selection bias. Further prospective studies are suggested to shed more light on this matter.

Ethical Considerations

Compliance with ethical guidelines

The present study was approved by the human research ethics committee of the Faculty of Medicine, Prince of Songkla University, Songkhla, Thailand (REC No. 64-477-10-1). The present study did not require informed consent from patients because the study design was a retrospective approach. Therefore, an informed consent waiver statement and the human research ethics committee of the faculty of medicine, Prince of Songkla University waived the need for informed consent.

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Authors' contributions

Conception and design: Thara Tunthanathip; Data Collection, data analysis and interpretation: Thara Tunthanathip and Anukoon Kaewborisutsakul; Drafting the article: All authors; Critically revising the article: Thara Tunthanathip, Sakchai Sae-heng and Thakul Oearsakul; Reviewing and final aproval of the submitted version of the manuscript: All authors.

Conflict of interest

The authors declare that there were no conflicts of interest.

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