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Original Article

Prediction of vascular complications in free flap reconstruction with machine learning

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Abstract: Objective: This study aims to explore the risk factors of vascular complications following free flap reconstruction and to develop a clinical auxiliary assessment tool for predicting vascular complications in patients undergoing free flap reconstruction leveraging machine learning methods. Methods: We reviewed the medical data of patients who underwent free flap reconstruction at the Affiliated Hospital of Zunyi Medical University retrospectively from January 1, 2019, to December 31, 2021. Statistical analysis was used to screen risk factors. A training data set was generated and augmented using the synthetic minority oversampling technique. Logistic regression, random forest and neural network, models were trained, using this dataset. The performance of these three predictive models was then evaluated and compared using a test set, with four metrics, area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, and specificity. Results: A total of 570 patients who underwent free flap reconstruction were included in this study, 46 of whom developed postoperative vascular complications. Among the models tested, the neural network model exhibited superior performance on the test set, achieving an AUC of 0.828. Multivariate logistic regression analysis identified that preoperative hemoglobin levels, preoperative fibrinogen levels, operation duration, smoking history, the number of anastomoses, and peripheral vascular injury as statistically significant independent risk factors for vascular complications post-free flap reconstruction. The top five predictive factors in the neural network were fibrinogen content, operation duration, donor site, body mass index (BMI), and platelet count. Conclusion: Hemoglobin levels, fibrinogen levels, operation duration, smoking history, and anastomotic veins are independent risk factors for vascular complications following free flap reconstruction. These risk factors enhance the ability of machine learning models to predict the occurrence of vascular complications and identify high-risk patients. The neural network model outperformed the logistic regression and random forest models, suggesting its potential to aid clinicians in early identification of high-risk patients thereby mitigating patient suffering and improving prognosis.

Keywords: AI, machine learning, free flap, vascular complication, risk factors, risk prediction model

Introduction

With the advancement of microsurgical technology, free flap reconstruction has emerged as a primary method for repairing damaged wounds, reconstructing affected areas, and enhancing appearance [1]. Studies have shown that the success rate of flap reconstruction is increasing annually. Despite these advancements, vascular complications still occur at an incidence rate of 10% to 30% following flap reconstruction [2]. Vascular complications, such as vascular spasm or thrombosis after microsurgical anastomosis of small vessels, lead to insufficient arterial perfusion or venous drainage of transplanted tissues, causing tissue congestion or ischemia [3]. This could lead to the patient returning to the operating room, increasing the risk of flap reconstruction failure, and thus increasing the patient's postoperative complications, hospital stay, economic burden, and mental stress [4, 5]. Currently, machine learning methods, including the random forest model, logistic regression model and support vector machine have been utilized to predict the likelihood of flap reconstruction

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failure. However, deep learning models have not been extensively applied in predicting vascular complications. Thus, this study introduces a risk warning model based on deep learning for patients undergoing free flap reconstruction, aiming to provide technical tools and a reference for clinical evaluation and treatment.

Patients and methods

Study population

In this study, medical records of patients with free flap reconstruction were retrospectively collected. The data for this study were obtained from patients who treated at the Affiliated Hospital of Zunyi Medical University between January 1, 2019, to December 31, 2021. Patient ages ranged between aged 18-85 years. The following patients were excluded: 1) patients lacking complete clinical data, and 2) patients who received adjacent or pedicle tissue flaps. Research personnel, after receiving standardized training, utilized uniform baseline collection forms. Forms were filled out to catalogue relevant patient information and subsequently rechecked in the collection to ensure accuracy.

Clinical data

The clinical data collected from patients who underwent free flap reconstruction at the Affiliated Hospital of Zunyi Medical University from January 1, 2019, to December 31, 2021, included preoperative variables such as gender, age, height, weight, body mass index (BMI), history of alcohol consumption, smoking history, presence of diabetes, history of radiotherapy/chemotherapy, American society of Anesthesiologists (ASA) score, and preoperative biochemical indicators including blood glucose, hemoglobin, white blood cell count, albumin levels, platelet count, fibrinogen levels, and prothrombin time. Intraoperative variables such as wound area, number of venous anastomosis, method of vascular anastomosis, donor and recipient areas, and intraoperative transfusion were also collected. Furthermore, postoperative indicators included volume of postoperative infusion volume, use of microcirculation drugs postoperatively, whether appropriate postoperative positioning was employed, pain scores, the surgeon's name, and outcome indicators.

Statistical analysis

Data were analyzed using SPSS 18.0 software. Metric data following a normal distribution were presented as mean ± standard deviation $(x \pm s)$, while metric data that conformed to a normal distribution were expressed as median and interquartile range $M(P_{25}, P_{75})$. Count data were described by frequency and percentage, and intergroup differences were tested using the chi-square test. The t-test was used for metric data that conformed to the normal distribution and homogeneity of variance in one-way analysis, and the rank sum test was used for metric data that did not conform to the normal distribution. Discrimination analysis was used to predict the performance of the models. Discrimination refers to the ability of a model to distinguish whether vascular complications occurred after free flap reconstruction in patients, and was quantified using the area under the receiver operating characteristic curve (AUC). Other revaluated indicators included accuracy, sensitivity, and specificity. $P<0.05$ was considered statistically significant.

Model construction

Anaconda 3 (Python 3.9) and third-party Python libraries such as Scikit-learn 0.24.2 were used for model development. Due to the imbalanced ratio of vascular complications to non-complications in this study, the Synthetic Minority Oversampling Technique (SMOTE) was utilized to oversample the less prevalent positive instances, aiming for balanced data. The data were randomly divided into two independent datasets: a training set and a testing set with a ratio of 6:4. The training set was sampled by SMOTE and used for model training, whereas the test set was used to evaluate the models. Logistic Regression (LR), Random Forest (RF), and Artificial Neural Network (ANN) were chosen as the prediction models, constructed using a machine learning library in Anaconda 3. For the Random Forest algorithm, model parameter optimization was performed using random search (GridSearch). For the Neural Network model, 10 variants were constructed using KerasTunner. The variant with the best performance was selected as the final ANN model. Upon training each model was assessed, using the testing set, and the performance of the three models were compared. To increase the number of predictive factors included, factors with a *P*-value <0.1 were con-

Table 1. Univariate analysis of continuous variables

Variable (unit)	$\bar{x} \pm s$ OR Median (P_{25}, P_{75})			t/Z	P
	Total N=570	Normal Group N=524	Complication Group N=46		
Age (years)	49.5 (42.0, 57.0)	49 (42, 57.0)	50.5 (39.8, 58.0)	-0.221	0.825
BMI (Kg/m²)	22.8 (20.8, 25.1)	22.6 (20.8, 25.0)	24.4 (21.3, 26.3)	-2.849	0.004**
Prothrombin time (S)	10.7 (9.7, 12.2)	10.7 (9.6, 12.2)	10.9 (9.7, 12.3)	-0.289	0.773
Haemoglobin (g/L)	115 (99, 130)	116 (100.3, 131)	106 (92.0, 119.0)	-3.552	<0.001***
Albumin (g/L)	34.6±4.7	34.7±4.7	34.3±4.7	0.513	0.608
Prealbumin (mg/L)	205.8±3.5	206.5±54.6	203.5±43.7	0.353	0.724
Blood glucose value (mmol/L)	5.55 (4.88, 6.58)	5.54 (4.88, 6.58)	5.79 (4.92, 6.78)	-0.329	0.742
Platelet count (10^9/L)	233.5 (185.0, 299.2)	232 (185, 297.8)	257.5 (214.8, 330.2)	-2.435	0.015**
Fibrinogen (g/dL)	3.27 (2.56, 4.26)	3.22 (2.52, 4.10)	4.83 (3.41, 5.61)	-5.343	<0.001***
Operating duration (min)	380 (305, 485)	380 (300, 480)	500 (427.5, 600)	-5.476	<0.001***
Trauma area (cm²)	50 (30, 96)	50 (30, 96)	63 (31, 109)	-1.146	0.246
Intraoperative blood loss (ml)	200 (100, 300)	200 (100, 300)	300 (137.5, 325)	-1.597	0.11
Postoperative infusion volume (ml)	2150 (1750, 2462.5)	2150 (1800, 2500)	1900 (1700, 2300)	-1.947	0.052*

*: $P<0.1$; **: $P<0.05$; ***: $P<0.01$. BMI: Body mass index; N: number.

sidered predictive variables and were included in the model.

Ethical statement

This study received approval from the Ethics Committee of the Affiliated Hospital of Zunyi Medical University (KLLY-2021-086).

Results

Patient characteristics

This study initially collected data from 600 patients undergoing free flap transplants patients. Thirty patients were excluded due to incomplete data, resulting in a final cohort of 570 patients. The average age of the participants was 49.5 years, comprising 408 males (71.6%) and 162 females (28.4%), with 284 smokers (49.8%) and 286 non-smokers (50.2%). Surgical exploration diagnosed 46 cases with vascular complications: 10 arteria, 33 venous, and 3 arteriovenous, culminating in an 8.07% rate of vascular complications in free flap surgeries. Out of 570 free flap transplants, 20 cases experienced necrosis, and leading to a free flap reconstruction success rate of 96.5%, aligning with rates reported in existing literature.

Results of statistical analysis

Predictor screening results: Univariate analysis performed on all factors related to vascular complications (**Tables 1** and **2**), identified 16 variables with $P<0.1$. All 16 eligible variables were included as the predictive factors. These included smoking history, body mass index, diabetes, preoperative platelet count, preoperative hemoglobin, preoperative fibrinogen, operation duration, postoperative day infusion volume, peripheral vascular disease, preoperative chemotherapy, intraoperative transfusion, venous anastomosis number, arterial anastomosis method, flap type, donor site, and recipient site.

Risk factor analysis: Multivariate logistic regression analysis was performed on the factors that exhibited $P<0.05$ in the univariate analysis (**Table 3**). The results indicated that preoperative hemoglobin, preoperative fibrinogen, operation duration, smoking history, number of venous anastomoses, and peripheral vascular disease were statistically significant ($P<0.05$), and acted as independent risk factors for postoperative vascular complications following free flap reconstruction.

Model results

Model performance: In this study, three machine learning-based models were developed to analyze the potential risk factors related to free flap vascular complications. The dataset was divided into training and test sets with a ratio of 6:4, using the Scikit-learn method for dataset splitting. The training set was

Table 2. Univariate analysis of categorical variables

Variable	Total N=570 [N (%)]	Normal Group N=524 [N (%)]	Complication Group N=46 [N (%)]	χ^2/Fisher's	*P*
Gender				0.995	0.318
Female	162 (28.4%)	146 (27.9%)	16 (34.8%)		
Male	408 (71.6%)	378 (72.1%)	30 (65.2%)		
Age				0.039	0.843
<60 years old	452 (79.3%)	415 (79.2%)	37 (76.1%)		
≥60 years old	118 (20.7%)	109 (20.8%)	19 (23.9%)		
Smoking				9.767	0.002**
Yes	284 (50.4%)	250 (47.7%)	34 (73.9%)		
No	286 (49.6%)	274 (52.3%)	12 (26.1%)		
Drinking				0.801	0.371
Yes	349 (61.2%)	206 (39.3%)	15 (32.6%)		
No	221 (38.8%)	318 (60.7%)	31 (67.4%)		
Hypertensive				0.085	0.77
Yes	55 (9.6%)	50 (9.5%)	5 (10.9%)		
No	515 (90.4%)	474 (90.5%)	41 (89.1%)		
Diabetes				7.284	0.007**
Yes	50 (8.8%)	41 (7.8%)	9 (19.6%)		
No	520 (91.2%)	483 (92.2%)	37 (80.4%)		
Peripheral vascular disease				6.35	0.014**
Yes	7 (1.2%)	4 (0.8%)	3 (6.5%)		
No	563 (98.8%)	520 (99.2%)	43 (93.5%)		
Radiotherapy/chemotherapy				3.16	0.078*
Yes	6 (1.1%)	4 (0.8%)	2 (4.3%)		
No	564 (98.9%)	520 (99.2%)	44 (95.7%)		
ASA score ≥3				0.357	0.55
Yes	261 (45.8%)	238 (45.4%)	23 (50%)		
No	309 (54.2%)	286 (54.6%)	23 (50%)		
Preoperative use of Doppler flowmetry				0.101	0.751
Yes	448 (78.6%)	411 (78.4%)	37 (80.4%)		
No	122 (21.2%)	113 (21.6%)	9 (19.6%)		
Intraoperative blood transfusion or not				2.845	0.092*
Yes	129 (22.6%)	114 (21.8%)	15 (32.6%)		
No	441 (77.4%)	410 (78.2%)	31 (67.4%)		
Number of anastomotic veins				5.543	0.019**
1	195 (34.2%)	172 (32.8%)	23 (50%)		
Two or more	375 (68.8%)	348 (67.2%)	23 (50%)		
Arterial anastomosis method				7.729	0.024**
End-End	513 (90%)	475 (90.6%)	38 (82.6%)		
Eed-Side	56 (8.8%)	49 (9.4%)	7 (15.2%)		
Vascular graft	1 (0.2%)	0	1 (2.2%)		
Venous anastomosis method				3.23	0.206
End-End	554 (97.2%)	509 (97.1%)	45 (97.8%)		
End-Side	13 (2.3%)	13 (2.5%)	0 (0%)		
Vascular graft	3 (0.5%)	2 (0.4%)	1 (2.2%)		
Flap type				9.005	0.04**
Skin flap	469 (82.3%)	434 (82.8%)	35 (76.1%)		
Fascial flap	15 (2.6%)	15 (2.9%)	0		

Myocutaneous flap	47 (8.2%)	39 (7.5%)	8 (17.4%)		
Skeletal muscle flap	31 (5.4%)	30 (5.7%)	1 (2.2%)		
Lymph node flap	8 (1.4%)	6 (1.1%)	2 (4.3%)		
Donor site				19.61	0.002***
Forearms	62 (10.9%)	61 (11.6%)	1 (2.2%)		
Femoral side	328 (57.5%)	298 (56.9%)	30 (65.2%)		
Gastrocnemius	63 (11.1%)	62 (11.8%)	1 (2.2%)		
Back	21 (3.7%)	16 (3.1%)	5 (10.9%)		
Iliac crest	43 (7.5%)	41 (7.8%)	2 (4.3%)		
Foot	43 (7.5%)	39 (7.4%)	4 (8.7%)		
Other	10 (1.8%)	7 (1.3%)	3 (6.5%)		
Recipient site				9.753	0.018**
Oral and maxillofacial	123 (21.6%)	115 (21.9%)	8 (17.4%)		
Upper limb	213 (37.4%)	203 (38.7%)	10 (21.7%)		
Lower limbs	230 (40.3%)	203 (38.7%)	27 (58.7%)		
Trunk	4 (0.7%)	3 (0.6%)	1 (2.2%)		
Postoperative Microcirculatory drugs				7.566	0.233
None	3 (0.5%)	3 (0.6%)	0		
1 kind	82 (14.4%)	78 (14.9%)	4 (8.7%)		
2 kinds	135 (23.7%)	127 (24.2%)	8 (17.4%)		
3 kinds	159 (27.9%)	143 (27.3%)	16 (34.8%)		
4 kinds	126 (22.1%)	110 (21%)	16 (34.8%)		
5 kinds	57 (10%)	55 (10.5%)	2 (4.3%)		
6 kinds	8 (1.4%)	8 (1.5%)	0		
Surgeon				0.95	0.924
Group I	106 (18.6%)	99 (18.9%)	7 (15.2%)		
Group II	98 (17.2%)	89 (17.0%)	9 (19.6%)		
Group III	115 (20.2%)	107 (20.4%)	8 (17.4%)		
Group IV	130 (22.8%)	118 (22.5%)	12 (26.1%)		
Group V	121 (21.2%)	111 (21.2%)	10 (21.7%)		

ASA: American society of anesthesiologists; N: number; χ^2: chi-square; *Fisher's*: Fisher's precision probability test. *: $P<0.1$; **: $P<0.05$; ***: $P<0.01$.

Table 3. Results of multi-factor logistic regression analysis

Variable	Odds ratio (95% *CI*)	*P*
BMI	1.126 (0.998, 1.271)	0.054
Fibrinogen	1.706 (1.283, 2.27)	<0.001*
Haemoglobin	0.987 (0.959, 0.998)	0.03*
Operating duration	1.004 (1.001, 1.006)	0.005*
Platelet count	1.003 (0.998, 1.007)	0.212
Smoking	4.430 (1.842, 10.65)	0.001*
Diabetes	2.335 (0.812, 6.712)	0.116
Peripheral vascular disease	19.45 (2.16, 175.07)	0.008*
Number of anastomotic veins	0.144 (0.056, 0.371)	<0.001*
Arterial anastomosis method		0.918
Flap Type		0.812
Donor site		0.119
Recipient site		0.098

BMI: Body mass index; *CI*: Confidence intervals; $^{*}P<0.05$.

comprised of 317 patients including 25 with complications, and the test set included 228 patients, with 21 experiencing complications. The SMOTE algorithm was applied to the training set, oversampling the minority class to achieve a 1:1 ratio between the complication and non-completion groups, resulting in balanced set of 317 cases with the complications. This sampled dataset was utilized to train the models, and the test set was used for validation. **Figure 1** presents the confusion matrix for each model, illustrating the prediction outcomes on the test dataset. The accuracy rates of the LR, RF, and ANN models were 78.5%,

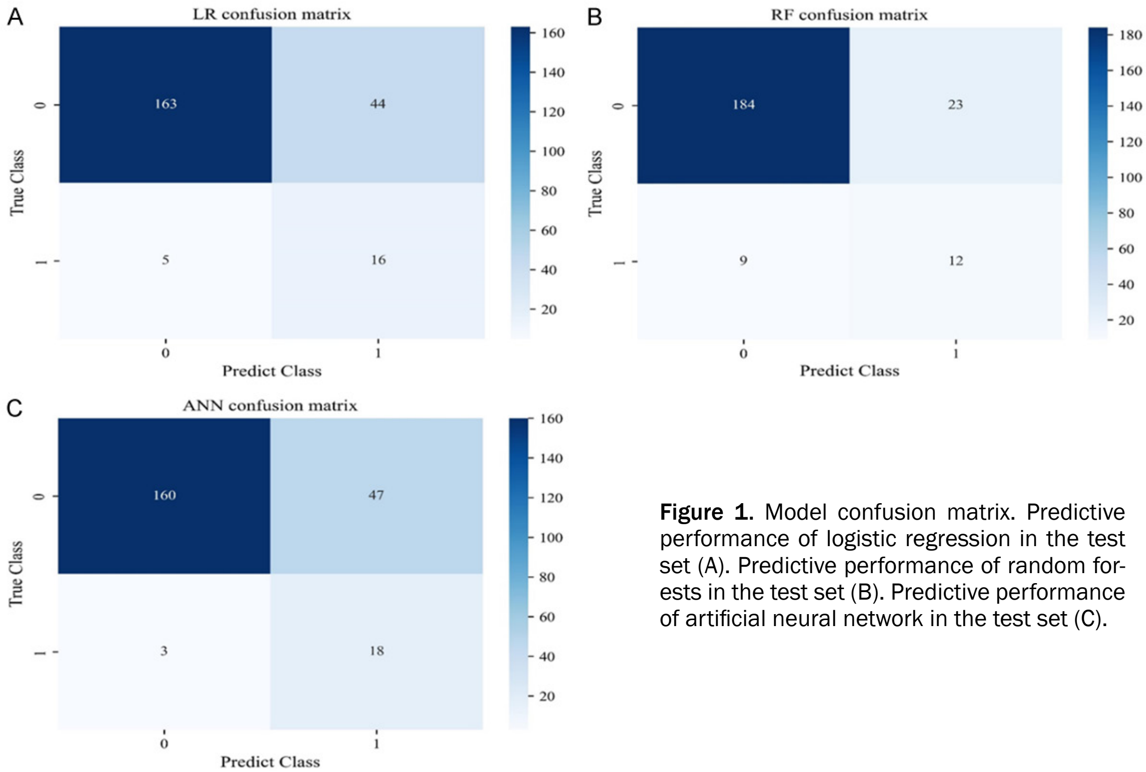

Figure 1. Model confusion matrix. Predictive performance of logistic regression in the test set (A). Predictive performance of random forests in the test set (B). Predictive performance of artificial neural network in the test set (C).

Table 4. Model performance evaluation

Evaluation metrics	Logistic Regression (LR)	Random Forest (RF)	Artificial Neural Networks (ANN)
Accuracy	0.785	0.86	0.781
Sensitivities	0.762	0.571	0.857
Specificity	0.787	0.889	0.773
AUC	0.775	0.73	0.828

AUC: area under the receiver operating characteristic curve.

85.5%, and 78.1%, respectively. The sensitivity values were 0.762, 0.571, and 0.857, respectively, while the specificity values were 0.787, 0.844, and 0.844, respectively. The AUC values were 0.775, 0.728, and 0.828, respectively, as detailed in **Table 4** and **Figure 2**.

The importance of model variables: **Figure 3** depicts the importance ranking of predictive factors in the Random Forest model for predicting vascular complications in flaps. The ranking was based on the feature importance index and the Gini index (G) within the Random Forest model. The five most influential factors in the Logistic Regression model were operation duration (G=0.194), fibrinogen level (G=0.169), platelet count (G=0.144), recipient site (G=0.129), and BMI (G=0.113). In the Random Forest model, the top five factors were operation duration (G=0.258), platelet count (G=0.153), preoperative fibrinogen level (G=0.129), BMI (G=0.115), and hemoglobin content (G=0.113). The top five predictive factors in the Neural Network model were fibrinogen content (G=0.111), operation duration (G=0.103), donor site (G=0.102), BMI (G=0.09), and platelet count (G=0.07).

Discussion

Factors associated with the development of vascular complication

Haemoglobin: Hemoglobin serves as a standard objective clinical indicator to assess anemia in patients. Hemoglobin levels below 130 g/L in men and below 120 g/L in women are

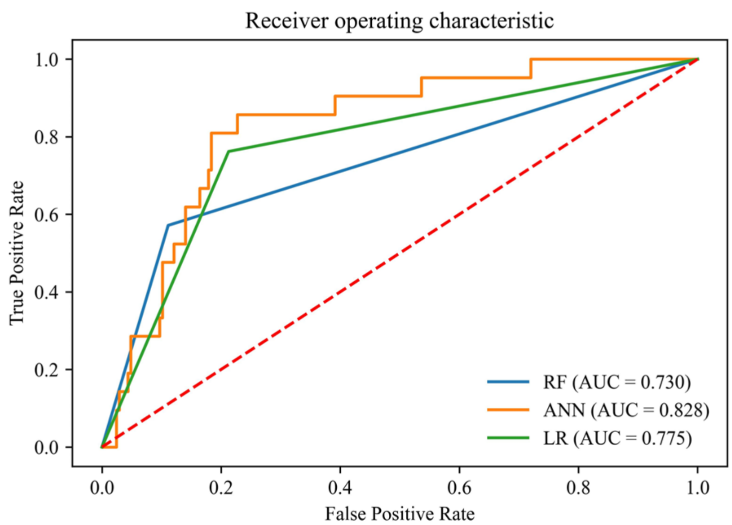

Figure 2. Model receiver operating characteristic (ROC) curve and the area under the receiver operating characteristic curve (AUC). LR: Logistic Regression; RF: Random Forest; ANN: Artificial Neural Network.

generally considered indicative of anemia. Several studies have reported that perioperative anemia increases the risk of flap graft failure, with a 0.5-fold reduction in flap failure for every 1 g/dL increase in perioperative hemoglobin concentration [6, 7]. These findings align with our study, which suggests that higher hemoglobin levels act as a protective factor against vascular complications. Haixuan Wu et al. [8] demonstrated that low hemoglobin levels contribute to higher incidence of complications post-flap grafting. Consequently, they advocate for a moderate elevation in hemoglobin levels to maintain postoperative levels above ten g/dL, facilitating early recovery of patients post-flap grafting [8, 9]. However, specific guidelines for perioperative blood transfusion in patients with grafts remain undefined. Other research indicates that perioperative blood transfusions may elevate the risk of postoperative infections [10].

Fibrinogen: Fibrinogen is crucial for platelet coagulation, and evidence suggests that a hypercoagulable state elevates thrombosis risk in patients following free flap grafting [11]. The results of this study found that high preoperative fibrinogen levels increase the risk of vascular complications with a 1.7-fold rise in the risk of flap vascular complications for every 1 g/dL increase in fibrinogen concentration. This suggests that elevated fibrinogen concentrations can lead to increased blood viscosity, potentially inducing atherosclerosis development, and slowing down blood circulation, thus raising thrombosis risk [12]. This is consistent with previous results where high fibrinogen levels were associated with a hypercoagulable state, increasing susceptibility to thrombosis and subsequent complications [13].

Smoking: Smoking has been identified as an independent risk factor for vascular crises. This study indicates that smokers are 4.43 times more likely to experience vascular complications than non-smokers. Smoking disrupts normal vascular physiology, induces vasospasm, and diminishes blood flow to the surgical incision site [14, 15]. Additionally, nicotine from tobacco irritates blood vessels, causing vasoconstriction, which reduces the blood supply to the recipient area thereby compromising the delivery of adequate oxygen and nutrients to the reconstructed skin flap. Therefore, patients should be advised to cease smoking before surgery and remain smoke-free in the hospital [16].

Operation duration: This study reveals that extended operative duration is associated with an increased risk of vascular complications following flap grafting; increase in operative duration can result from various factors, including the complexity of the procedure, and limited experience of the operating surgeon [17]. Ishimaru et al. [18] analyzed data from 2846 patients in Japan's national databases and found a correlation between longer operative duration and free flap failure. Similarly, a study by Sanati-Mehrizy et al. [17] involving 2013 patients in 2015 identified an association between flap failure and operative duration through univariate analysis.

Peripheral vascular disease: Peripheral vascular disease is characterized by atherosclerotic stenosis or occlusive lesions in the lower extremity arteries, leading to chronic or acute ischemic symptoms in the lower extremities. This includes asymptomatic atherosclerotic disease, intermittent claudication, severe limb ischemia, and acute limb ischemia [19]. Ishimaru et al. [18] found in their study on head

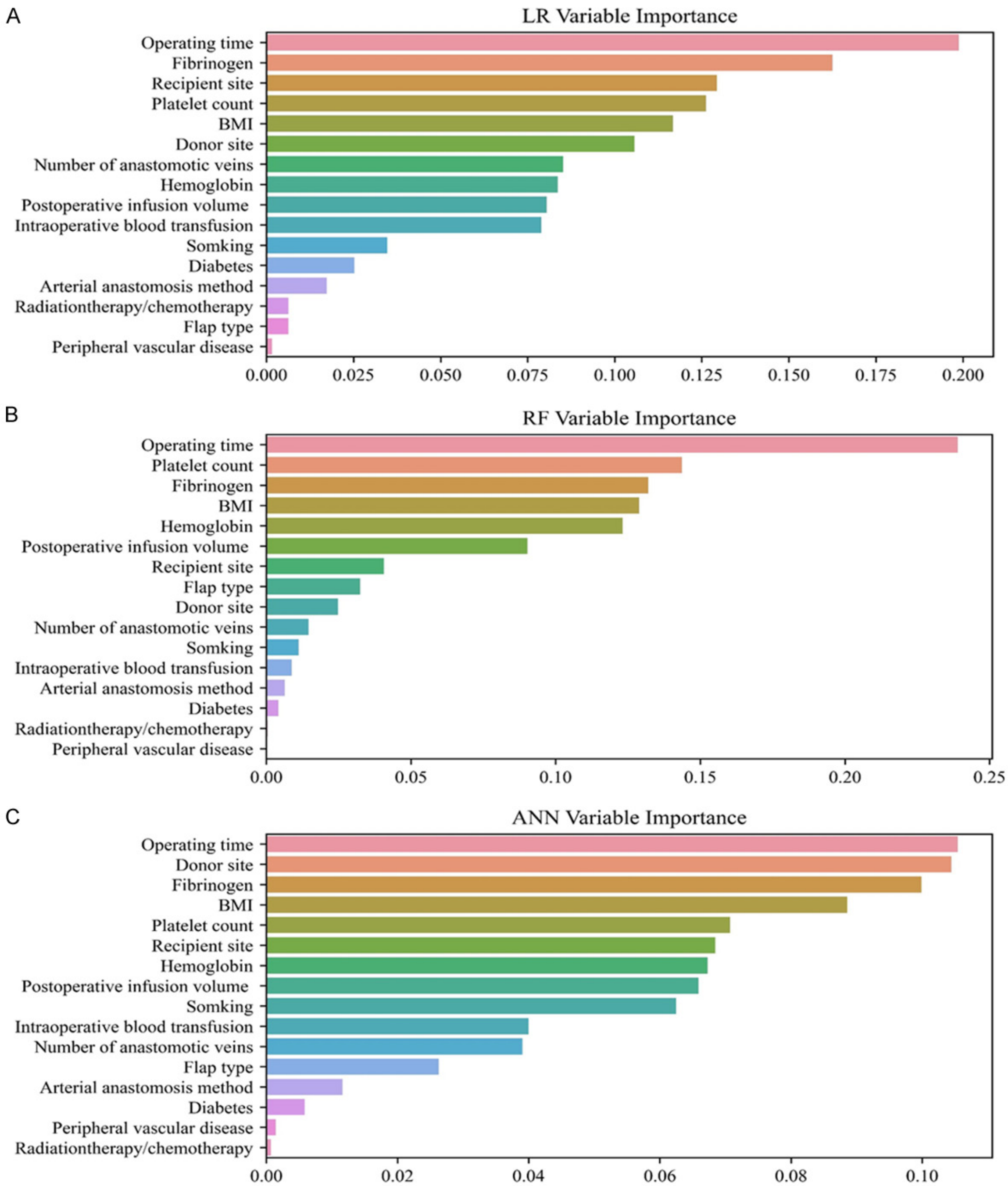

Figure 3. Model feature importance. Ranking of importance of predictors of logistic regression (A). Ranking of importance of predictors of random forests (B). Ranking of importance of predictors of artificial neural network (C).

and neck flap grafting that patients with peripheral vascular disease were more likely to experience flap failure, a finding consistent with our study. Peripheral vascular disease is primarily associated with advanced age, diabetes mellitus, and hypertension. Additionally, other studies [20] have identified diabetes mellitus as an independent risk factor for vascular complications, likely due to its contribution to microvascular damage in patients, thereby elevating thrombosis risk post-flap grafting.

Number of venous anastomoses: Lee et al. [21] conducted a retrospective analysis in 2016 on patients undergoing anterior femoral episcleral flap repair after oral cancer resection. They discovered that while performing anastomoses on two veins it took approximately 30 minutes longer than anastomosing a single vein, the incidence of vascular complication and venous vascular occlusion was significantly reduced. Our multifactorial analysis indicated that having more than one venous anastomosis acts as a protective factor against the development of vascular complications. Some investigators suggest that anastomosing two veins rather than one enhances flap venous return. In the event of an obstruction in one vein, the other vein can continue to facilitating venous blood return, leading to more efficient blood flow, decreasing the risk of flap bruising and improving flap survival [22]. This effectively reduces the risk of flap stasis and enhances flap survival.

Impact of unbalanced data

The cohort data in this study exemplify data imbalance, with a significant discrepancy between the number of cases in the minority class (n=46) and the majority class (n=524). Models trained on imbalanced data often fail to fully capture the characteristics of the minority class and generally exhibit poor performance when applied to new datasets. Such models are prone to "overfitting", which tends to underestimate the probability of events in low-risk patients and overestimate the probability of events in high-risk patients, potentially impacting clinical decision-making [23]. SMOTE is an oversampling technique that creates artificial samples based on actual samples in the dataset, theoretically reducing the overfitting of the model [24]. Since data imbalance can adversely affect the performance of predictive models, we improved the distribution of majority versus minority classes by using the SMOTE method to fit the model using the sampled training data, enabling the model to learn as comprehensively as possible about the patterns of vascular crisis occurrences.

Significance of factors in each model

Univariate analysis revealed that the occurrence of free flap graft vascular complications is driven by multiple factors. In the variable importance rankings, the top five risk factors across the three models were broadly similar, with variations primarily in the weight assigned to each predictor. Surgery duration and fibrinogen levels were identified as significant factors in all three models, which align with risk factors pinpointed by multifactorial logistic regression. While some top-ranked factors, such as platelet count and BMI, did not match those identified by multifactorial logistic regression, other studies have highlighted BMI, ischemic duration, and platelet count as risk factors [4, 25]. Sinha, S. et al. [25] advised caution when performing free flap grafting on obese patients with high BMI. Additionally, prolonged ischemic duration for free flaps, leading to ischemia-reperfusion injury can heighten the risk of postoperative complications and eventual flap graft failure. However, ischemic time was not included in our study due to a significant number of missing values. Elevated platelet counts have been recognized as a thrombosis risk factor, as demonstrated in studies by Stevens, M.N. et al. and Kalmar, C.L. et al. Stevens, M.N. et al. which found the risk of flap graft failure increased 2.67-fold for every 1-unit rise in platelet count in patients with head and neck surgical free flap grafts while Kalmar, C.L. et al. discovered the association of thoracic microvascular repair failure with platelet counts in women [26, 27].

The Neural network model has better predictive efficacy for free flap crises

Previous studies on free flap graft complications primarily utilized traditional logistic regression-based methods [28, 29] or decision tree algorithms and with neural network algorithms yet to be adopted [30]. Neural network algorithms are more adaptable than logistic regression, decision trees, and support vector machines can be continuously trained on a large influx of updated samples. Their "black box" nature also makes them more accessible for clinical staff to understand and utilize [31]. In our study, the neural network model demonstrated accuracy, sensitivity, and specificity 0.781, 0.857, and 0.773, respectively, with an AUC of 0.828. These results indicate that neural network models can exhibit strong capabilities in recognizing the occurrences of vascular crises in postoperative patients and this model could achieve a certain degree of accuracy in predicting the future of vascular crises. Additionally, we observed a high accuracy (0.855) and specificity (0.884) in predicting vascular complications using the random forest suggesting substantial efficacy in determining the absence of complications. However, with a sensitivity of 0.571, the model showed limitations in predicting the likelihood of developing vascular complications. The AUC value of the random forest model was 0.730 suggesting moderate capability in detecting vascular complications when considering the combined sensitivity and specificity. The performance of the tree model in our study is consistent with results from other studies. Shi YC et al. [30] developed three machine learning models to predict microvascular reconstruction failure with AUC values ranging from 0.7 to 0.77. O' Neill et al. [32] used a random forest model to predict the occurrence of flap graft failure in breast microvascular reconstruction patients and with an AUC of 0.67. These outcomes were comparable to the results from the machine learning model generated in this study. The predictive model constructed in this study primarily assists clinical staff in prevention. In the future, the model can be combined with indicators observed from the flap to predict the occurrence and progression of vascular crises. Additionally, due to the subjective nature of color observation of the flap, the development of image recognition-based tools for assessing complications could be developed in the future.

Summary

Free flap grafting is a well-established technique for trauma repair, and timely identification and recognition of patients at risk for postoperative complications can significantly enhance the success rate of flap grafting [33]. The risk factors associated with vascular complications after free flap reconstruction, identified through logistic regression analysis, enable clinical workers to implement targeted care strategies for patients with varying risk profiles, crucially contributing to the reduction of vascular complication rates post-reconstruction. The prediction model constructed in this study is mainly used to assist clinical staff in prevention. In the future, the model can be combined with the observation index of the skin flap to predict the occurrence and progression of vascular crisis. Moreover, since the observation of skin flap color is influenced by the subjective judgment of observers, development of an auxiliary assessment tool for vascular crisis based on image recognition could also be pursued in the future. Our study was a single-center retrospective study. Despite achieving high discrimination, the models incorporated only a limited number of factors and were based on a constrained case set. Future efforts should focus on capturing a more comprehensive full pattern of vascular complications in free flaps. To optimize and validate their effectiveness, extensive, multicenter studies with larger sample sizes are essential.

Conclusion

In conclusion, hemoglobin, fibrinogen, operation duration, smoking history, and anastomotic veins are independent risk factors for vascular complications. These risk factors can help machine learning models predict the occurrence of vascular complications and identify high-risk patients. Among the three models, the neural network model outperformed the others, offering clinicians a superior tool for early identification of high-risk patients, potentially reducing patient suffering and improving prognoses.

Disclosure of conflict of interest

None.

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