Tatsuya Hasegawa*, Toshiyuki Nakanishi, and Koichi Fujiwara
* Nagoya City University, Japan
E-mail: author1 t.hase@med.nagoya-cu.ac.jp. Tel: +81-52-851-5511
Nagoya City University, Japan
E-mail: nakanishi.anest@gmail.com Tel: +81-52-851-5511
Hokkaido University, Nara Institute of Science and Technology, Japan
E-mail: fujiwara.koichi@es.hokudai.ac.jp Tel: +81- 11-706-9417

Abstract**—** In extracorporeal membrane oxygenation (ECMO) management, preventing complications such as thrombosis and bleeding is essential. While circuit exchange is necessary to prevent serious outcomes, there are no standardized guidelines, and decisions are typically based on institutional protocols and clinical judgment. This study aims to develop a predictive model for the timely exchange of ECMO circuits in pediatric patients. We retrospectively analyzed data from 84 pediatric veno-arterial (VA)ECMO cases between April 2016 and March 2024, including 45 exchange events in 24 patients. Sixteen ECMO-related and laboratory features were selected. Abnormal data were defined as those within six hours before circuit exchange (270 samples), and normal data were obtained from periods excluding initiation, weaning, and pre-exchange intervals (13,749 samples). Due to the highly imbalanced dataset, we used XGBoost with five-fold cross-validation (80% training / 20% testing split), optimizing for G-mean through grid search. The model achieved a mean G-mean of 0.81 (SD 0.03), sensitivity of 0.91 (SD 0.02), and specificity of 0.72 (SD 0.07), demonstrating sufficient predictive performance for potential clinical application.

I. Introduction

Extracorporeal membrane oxygenation (ECMO) is used to treat critically ill patients and has become an important treatment strategy in intensive care. In Japan, ECMO is an essential tool for cardiac support, particularly after cardiac surgery or cardiac arrest. Its role has expanded to include respiratory failure in recent years, and ECMO played a crucial role in saving many lives during the COVID-19 pandemic that began in 2019 [1]. However, complications associated with ECMO therapy, such as bleeding, thrombosis, infection, and mechanical failure, can be life-threatening, and even when not fatal, they may significantly impair post-treatment activities of daily living (ADL) [2]. Therefore, preventing these complications is crucial for improving the safety of ECMO therapy. This study focuses on thrombosis, which is a major complication [3].

ECMO consists of cannulas (for drainage and reinfusion), a circuit, and a membrane oxygenator. In this study, the term “circuit” refers collectively to the tubing, oxygenator, and associated components. Normally, blood tends to activate the coagulation cascade and form thrombi when exposed to the surfaces of artificial structures, including the ECMO circuit. Thrombus formation within an ECMO circuit is a well-recognized complication. Anticoagulants were administered to prevent thrombus formation in the ECMO circuit. However, excessive anticoagulation poses a significant risk of bleeding, necessitating a balance between prevention of thrombosis and avoidance of bleeding. If thrombosis increases, it is necessary to exchange the circuit containing the thrombus before serious complications occur (e.g., ischemic stroke, cerebral hemorrhage, or sudden mechanical failure). There are currently no clear guidelines for ECMO circuit exchange, including those from the Extracorporeal Life Support Organization (ELSO), which manages the International ECMO Registry [4]. Although several reports have examined the amount and location of thrombosis within the circuit after replacement, clear criteria for circuit exchange have not been established [5]. Consequently, circuit exchange is typically based on institutional protocols and clinical judgment.

Early circuit exchange may help prevent complications; however, this procedure has inherent risks. Circuit exchange increases the risk of hemorrhagic complications by diluting blood with non-blood priming solutions, leading to coagulopathy and triggering systemic inflammatory responses that further disrupt the coagulation balance. Dilutional coagulopathy is of particular concern in pediatric patients; therefore, frequent circuit exchange should be avoided whenever possible. No specific cause has been identified, but frequent circuit exchanges have been shown to increase mortality ［6］.

The aim of this study is to develop a predictive model to support clinicians in decision-making regarding ECMO circuit exchange in pediatric patients.

II. Methods

This was a retrospective study that used data from a single-center pediatric hospital in Japan. The study included patients on veno-arterial (VA)-ECMO who were admitted to the ICU between January 2016 and March 2024. Patients over 18 years old or those undergoing Veno-Veno (VV) ECMO were

979-8-3315-7206-8/25/$31.00 ©2025 IEEE

excluded. In this study, all circuit-related interventions-including complete circuit exchanges, artificial lung (oxygenator) exchanges, or other partial component exchanges-are collectively defined as "circuit exchange". No distinction is drawn between urgent and elective procedures. This retrospective study used electronic health record data collected on a daily basis, making neither the evaluation of outcomes nor the collection of predictor data blinded. No formal sample size calculation was performed and the maximum available data were extracted from the study period. The study protocol was approved by our institutional review board (approval number 2024057).

Data were collected from electronic health records, including laboratory tests, vital signs, and patient observations by healthcare professionals. Sixteen features were used in this study, consisting of the ECMO-related parameters and the blood sample measurements. The ECMO-related parameters included visual thrombus (thrombosis), pump speed (revolutions per minute), flow (VAFlow), drainage pressure, pre- and post-membrane CO_2 difference (deltaCO_2), post-membrane PO_2 (postPO_2), and pressure difference across the membrane (deltaP). The blood sample features included platelet count (Plt), fibrinogen level, activated partial thromboplastin time (APTT), prothrombin time–international normalized ratio (PT-INR), fibrinogen degradation products (FDP), D-dimer, pH, blood lactate level, and base excess (BE). Among the ECMO-related parameters, the pre- and post-membrane pressures were measured every minute, while the others were measured at hourly intervals. Blood samples were taken as necessary, typically at intervals of 4–6 hours. Sixteen variables were used in clinical practice as important factors for evaluating thrombosis and all variables were used to create the model. We excluded clinically implausible values (e.g., APTT of 160 seconds or flow of 3000 ml/min).

First, we created a table with one row per hour from the start to the end of the ECMO support. Next, the collected data were entered into newly created rows. Because there was a time gap between the row timestamps and measurement times, each value was assigned to the row with the closest timestamp. If the timestamp of the newly created row was later than the measurement time, the value was assigned to the previous row instead to avoid inserting data into a future time point. For variables measured multiple times within an hour, we used the average of the values recorded up to that time point, ensuring that no future data were included.

Blood tests generally have a wide measurement interval of approximately 6-8 hours, and the measurement interval varies depending on the patient. Time-Dependent Iterative Imputation (TDI), a method that integrates forward replacement and multivariate imputation by weighting the time and frequency from observations to impute missing values, was used in this study as a complementary approach that takes these factors into consideration [7]. After imputation with TDI, some values become negative. For variables that could not be negative in clinical settings, these values were corrected to zero. For comparison, we also used a forward-filling approach as a baseline method. To avoid future data leakage, the TDI algorithm was modified to use only past data during imputation. Variables that could not be imputed by either method were left as missing.

The criteria for circuit replacement are as follows:

1. free hemoglobin ≥ 100 mg/dl
2. Floating thrombus in the arterial side of the circuit
3. pre- and post-membrane pressure gradient ≥ 50 mmHg
4. post-membrane PaO_2 < 200 mmHg (FiO_2 1.0)
5. pre- and post-membrane $PaCO_2$ difference < 10 mmHg

The decision was made by a medical team led by an intensivist based on these criteria.

"Abnormal" data were those within 6 hours before circuit exchange. "Normal" data were the rest, excluding data within 12 hours of ECMO start, within 12 hours before the first exchange, and within 12 hours before ECMO end. (Figure 1)

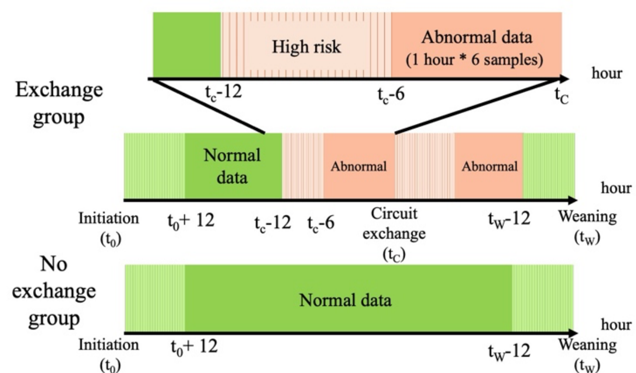

Fig.1 illustration of dataset

Some reports indicate that circuit exchange is necessary in only 16% of cases [8], indicating that the frequency of exchange is relatively low. In addition, the time required for circuit exchange is very short compared to the total duration of ECMO support; therefore, the data are expected to be imbalanced. The prediction model uses XGBoost, which is a gradient boosting framework. To address class imbalance, the scale_pos_weight parameter was applied to up-weight the minority class during training. Five-fold cross-validation was employed, splitting the data into 80% training sets and 20% test sets per fold. We calculated the average of five cross-validations and evaluated the model. Hyperparameter optimization was conducted using grid search within each training fold, with G-mean used as the scoring metric. The search space consisted of the number of estimators (n_estimators) set to 50, 100, or 200; the learning rate (learning_rate) was set to 0.01, 0.1, or 1.0; and the maximum

depth of the base estimator (max_depth) was set to 3, 5, or 7. In addition, to address class imbalance, the scale_pos_weight parameter was calculated as the ratio of negative to positive samples in the training set and applied accordingly.

Our goal is to create a model that predicts circuit exchange within 6 hours in advance. When circuit exchange was determined based on fulfilling three or more of the five facility-defined criteria, and the same dataset as this study was used, the G-mean was approximately 0.3. Therefore, considering the class imbalance in the data and the low G-mean of 0.3 obtained using the facility-based criteria, we set a target G-mean of 0.7 for this study, which we consider to be a reasonable threshold for practical use in clinical settings. Statistical analysis was performed using the chi-square test for categorical variables and the Mann-Whitney U test for other variables, with a significance level of $p<0.05$. All analyses, including model creation, were performed using Python (3.11.9).

III. Results

From January 2016 to March 2024, 99 patients underwent ECMO, and since some children required multiple treatments, there were 101 cases. Of these, 84 cases were selected after excluding 15 cases of VV-ECMO and two cases of VV-ECMO to VA-ECMO. Of these, 24 required circuit exchanges and 45 replacements were performed.

There were no significant differences between the exchange and non-exchange groups in terms of age at ECMO initiation (p=0.34), weight (p=0.58), length of ICU stays (p=0.35), number of deaths (p=0.41), or route of admission (p=0.44). However, the duration of ECMO support was significantly longer in the exchange group (p=0.0002). The results of blood sampling before the start of ECMO showed significant differences in APTT and fibrinogen. (table 1)

Table 1 Comparison Between Exchange and Non-exchange Groups

		Exchange group (n=24)		Non exchange group (n=58)		p
Age	(day)	123	[20-858]	309	[45-2222]	0.34
Weight	(kg)	5.3	[3.0-10.5]	7.4	[3.2-19.0]	0.58
Length of ICU	(day)	25	[12-35]	19	[10-31]	0.35
ECMO duration	(day)	5	[3-11]	3	[1-6]	0.0002
Death in the ICU		12		21		0.41
Admission source	operating room	4		16		0.44
	Emergency department	20		42		
APTT		47.4	[46.6-57.4]	36.9	[33.5-50.6]	0.03
D-dimer		3.5	[0.7-27.1]	2.1	[1.3-3.5]	0.88
FDP		17.4	[2.5-50.6]	5.3	[2.8-11.9]	0.97
LDH		462	[303-1229]	412	[273-654]	0.3
PT-INR		1.24	[1.09-1.69]	1.22	[1.06-1.38]	0.59
Tbil		0.8	[0.48-3.2]	0.7	[0.4-1.4]	0.56
Fib		123	[81-155]	191	[152-221]	0.03
Plt		28.9	[7.1-40.6]	26.5	[12.5-39.3]	0.76

This study defined circuit exchange as an abnormal event and classified data from up to six hours preceding the exchange as abnormal. (Fig.1). As a result, there were 270 abnormal data points and 13,749 normal data points for one row per hour. The median number of data points per hour was 96 (IQR 59-167).

The XGBoost model achieved a mean G-mean of 0.81 (SD 0.03), sensitivity of 0.91 (SD 0.02), and specificity of 0.72 (SD 0.07). Using forward imputation, the results were as follows: the G-mean was 0.79 ±0.02, which was lower compared to TDI.

Circuit exchange is a relatively rare clinical event during ECMO management, typically occurring only under specific and critical conditions. The dataset used in this study was highly imbalanced, with abnormal cases accounting for only 1.9% of the total data. This imbalance affected the model's ability to detect abnormal events consistently, resulting in a relatively low F1 score of 0.12 (SD 0.03) and PR-AUC of 0.16 (SD 0.05), despite achieving high sensitivity of 0.91 (SD 0.02).

A confusion matrix aggregating the predictions across all five cross-validation folds is shown in Fig.2. The model correctly identified 245 out of 270 abnormal cases, with 25 false negatives. Among the 13,749 normal cases, 9851 were correctly predicted and 3898 were falsely classified as abnormal.

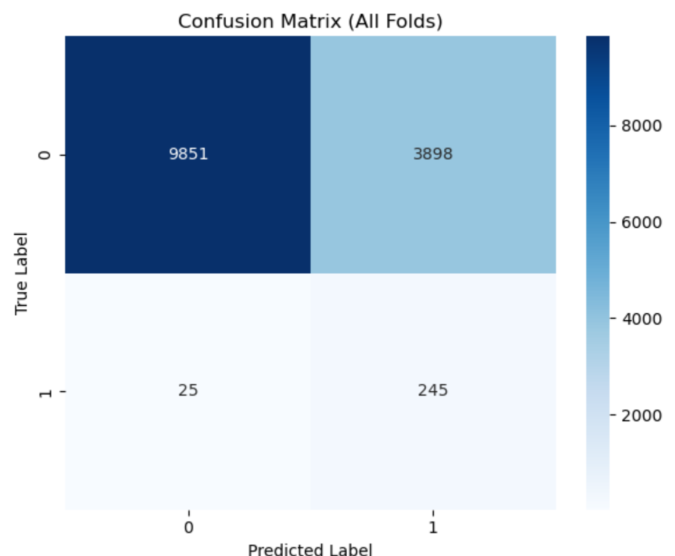

Fig.2 Confusion matrix of this model

Feature importance analysis (Fig. 3) revealed that ECMO-related variables indicating membrane oxygenator function, such as the pressure gradient (deltaP) and CO_2 difference (deltaCO_2) across the oxygenator, also had high importance,

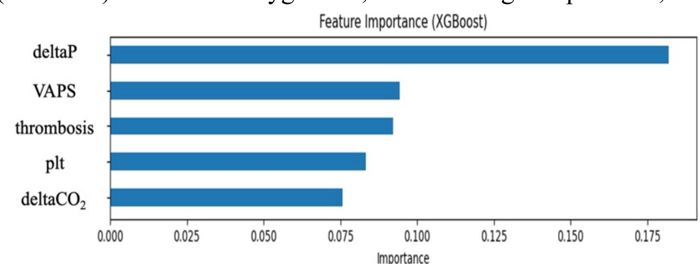

Fig.3 Top five important features in the model

supporting their role as markers of impaired oxygenator performance due to thrombus. In contrast, variables such as VAFlow and drainage pressure were less important. These parameters are influenced by multiple factors, including fluid balance, cannula position, and overall hemodynamic status and may therefore be less specific indicators of thrombus formation.

IV. Discussions

A predictive model for ECMO circuit exchange was created using the data from a single institution. The model developed in this study had a G-mean of 0.81, which is considered clinically acceptable compared with the conventional standard G-mean of approximately 0.3. The model can be applied on an hourly basis, allowing clinicians to update the blood test data and re-run the evaluation whenever they suspect the need for circuit exchange. This makes it a practical tool for determining circuit exchange in clinical settings.

The dataset used in this study was imbalanced, with a large amount of normal data. This is because of the clinical characteristics of ECMO, where circuit exchange events are rare, making it difficult to collect abnormal data. If there are even fewer abnormal data points, we will have to choose an anomaly detection method. In this case, abnormal data accounted for 1.9% of the total, and the binary classification was feasible. The G-mean is considered an appropriate evaluation metric for imbalanced data, as it effectively balances sensitivity and specificity. In practice, although specificity was high, sensitivity was low, and evaluation using the G-mean was deemed appropriate.

The variables used in this study were those used in clinical practice to determine circuit exchange. Although 16 variables were used in this study, it may be better to use fewer variables for implementation in clinical practice. This will be addressed through external validation in the future. Another option would be to limit the number of variables to only those related to ECMO, thereby confirming the importance of the blood collection test. Variable selection is a future task for the search for variables important for implementation and circuit exchange in clinical practice.

In this study, we used XGBoost to address data imbalance. XGBoost can incorporate class imbalance directly through the scale_pos_weight parameter, which adjusts the impact of the minority class during training. Additionally, its robustness, regularization capabilities, and efficiency make it well-suited for noisy or small clinical datasets. These characteristics made XGBoost an appropriate choice for our analysis [9].

We used TDI to impute the missing values [7]. In clinical practice, the most recent measurements at the time are used to assess the patient's condition. As this approach is similar to forward completion, we chose forward substitution to complement missing values. Some variables had sampling intervals of 8-12 hours, which could not be adequately addressed by forward replacement. Therefore, we used TDI, which combines forward and multivariate imputation. Compared to forward replacement using the same dataset, G-mean was improved. When using medical data, missing value imputation is often a challenge. In this study, we believe that TDI enables reasonable imputation. TDI considers the timing and frequency of measurements, which is especially important in clinical settings where measurement intervals are irregular and time gaps vary. These characteristics of the TDI likely contributed to the improved imputation accuracy of our dataset.

According to the feature importance analysis, ECMO parameters, such as pre- and post-oxygenator pressures and carbon dioxide removal, showed high feature importance. This indicated deterioration of the artificial lung due to thrombosis, which was consistent with its clinical significance. Other variables were also affected by circuit thrombosis, but their importance in the model was low. This may be because medical staff monitored the patient’s condition and adjusted these values as needed, keeping them within a safe range and making it harder for the model to detect changes related to thrombosis. This suggests that using the rate of change in these parameters may better reflect circuit condition, and incorporating trend-based features could enhance the model in future studies.

Although most blood sampling variables showed relatively low importance in our analysis, D-dimer and FDP were clinically important markers of thrombosis [10]. However, these markers are not highly sensitive to early changes; therefore, frequent testing offers limited clinical benefits. Therefore, the sampling frequency did not adapt significantly to clinical changes, which may have contributed to its lower importance in our analysis.

This study had several limitations. First, it was conducted using data from a single institution. Although cross-validation was performed, external validation with data from other centers is needed. Second, some entries were manually input by medical staff. While obvious outliers were handled, it was not possible to retrospectively verify the overall data accuracy. Third, due to preparation and staffing, there was often a time lag of several hours between the decision to exchange circuits and the actual exchange. Therefore, data from up to six hours before the exchange were labeled as abnormal; however, this varied between cases and institutions and could not be fully standardized. In this study, the timing of the circuit exchange decisions was not recorded, and some clinical data had to be entered manually. These limitations can be overcome by prospectively and systematically collecting such information.

This preliminary study utilized only the XGBoost algorithm. Oversampling and undersampling, which are commonly used with imbalanced data, need to be validated. The dataset is

highly imbalanced, and comparisons with anomaly detection methods will be made in the future [11].

V. Conclusions

A prediction model for circuit exchange in pediatric patients with ECMO was developed in this study, demonstrating sufficient predictive performance for potential clinical application, with a mean G-mean of 0.79. Future work will focus on improving the performance of the model by increasing the volume and diversity of data, expanding the feature set, and conducting external validation and prospective studies to further verify its clinical utility.

VI. Acknowledgment

The authors would like to thank Dr. Takanari Ikeyama of the Aichi Children's Health and Medical Center in Japan for his support with data collection and valuable advice on the study design.

References

[1] R. Barbaro, R. MacLaren, R. Diaz, et al., "Extracorporeal membrane oxygenation support in COVID-19: an international cohort study of the Extracorporeal Life Support Organization registry," Lancet, vol. 396, pp. 1071–1078, Oct. 2020.

[2] D. V. Pisano, J. P. Ortoleva, and P. M. Wieruszewski, "Short term neurologic complications in patients undergoing extracorporeal membrane oxygenation support: a review on pathophysiology, incidence, risk factors, and outcomes," Pulm. Ther., vol. 10, pp. 267–278, 2024.

[3] D.A. Murphy, L.E. Hockings, R.K. Andrews, C. Aubron, E.E. Gardiner, V.A. Pellegrino, A.K. Davis, "Extracorporeal membrane oxygenation–hemostatic complications," Transfusion Medicine Reviews, vol. 29, pp. 90–101, Apr. 2015.

[4] A. McMichel, C. L. Brogan, L. A. Dalton, et al., "2021 ELSO Adult and Pediatric Anticoagulation Guidelines," ASAIO J., vol. 68, pp. 303–310, 2022.

[5] C. Villalba, A. Gonzalez, E. R. Edelson, and B. J. Bacchetta, "Thrombosis in extracorporeal membrane oxygenation (ECMO) circuits," ASAIO J., vol. 68, pp. 1083–1092, 2022.

[6] N. Seliya, A. Abdollah Zadeh, and T. M. Khoshgoftaar, "A literature review on one-class classification and its potential applications in big data," Journal of Big Data, vol. 8, Article 122, Sep. 2021.

[7] O. Noy and R. Shamir, "Time-dependent iterative imputation for multivariate longitudinal clinical data," in Proc. Int. Conf. Learn. Representations (ICLR), 2023.

[8] T. Genty, S. Burguburu, A. Imbert, C. Roman, C. Wirth, J. Thès, and F. Stéphan, "Circuit change during extracorporeal membrane oxygenation: single-center retrospective study of 48 changes," Crit. Care, vol. 27, p. 219, 2023.

[9] G. Velarde, A. Sudhir, S. Deshmane, A. Deshmunkh, K. Sharma, and V. Joshi, "Evaluating XGBoost for Balanced and Imbalanced Data: Application to Fraud Detection," arXiv:2303.15218, Mar. 2023.

[10] C. Dornia, A. Philipp, S. Bauer, C. Stroszczynski, A. G. Schreyer, T. Müller, G. E. Koehl, and K. Lehle, "D-dimers are a predictor of clot volume inside membrane oxygenators during extracorporeal membrane oxygenation," Artif. Organs, vol. 39, no. 9, pp. 782–787, 2015.

[11] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM Computing Surveys, vol. 41, no. 3, pp. 1–58, Jul. 2009.