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ORIGINAL RESEARCH

Development and Validation of a Neonatal Hypothermia Prediction Model for In-Hospital Transport Using Machine Learning Algorithms: A Single-Center Retrospective Study

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Objective: This study aims to predict hypothermia during neonatal in-hospital transport using machine learning techniques, identify risk factors, rank their importance, and visualize the results, allowing healthcare providers to rapidly assess the probability of hypothermia risk during transport.

Methods: Clinical data of 9,060 neonates transported within a tertiary maternity hospital in Shanghai between January 2023 and June 2024 were collected, including maternal and neonatal data. Variables were selected using LASSO regression. Neonates were categorized into hypothermia and normal temperature groups based on their body temperature during transport, with 6:2:2 ratio for training, test and validation datasets. Six machine learning algorithms—Decision Tree (DT), Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Naive Bayes (NB)—were used to develop predictive models. The effectiveness was evaluated using area under the ROC curve (AUC), along with F1 score, accuracy, sensitivity, specificity, and Hosmer-Lemeshow calibration tests with Brier scores. The best-performing model was further analyzed for risk factors using SHAP plots.

Results: Among the neonates, 5,072 (55.98%) experienced hypothermia during transport. Ten risk factors were identified through univariate analysis and LASSO regression, including gestational age, weight, and immediate postnatal contact. The RF model demonstrated the best overall performance, achieving a training set AUC of 0.994 and an accuracy of 0.957, while the test set AUC and accuracy were 0.962 and 0.889, respectively.

Conclusion: Hypothermia incidence during neonatal in-hospital transport is relatively high. The RF-based prediction model demonstrated strong predictive and generalization capabilities, providing actionable guidance for early identification of neonates at risk of hypothermia during transport.

Keywords: Neonate, Hypothermia, Intra-hospital Transfer, Predictive Model, Machine Learning

Neonatal hypothermia is defined by the World Health Organization as a core temperature below 36.5°C due to various factors in newborns.[1] Due to characteristics such as a large body surface area, thin subcutaneous fat, and immature thermoregulatory mechanisms, newborns are highly susceptible to hypothermia when exposed to low ambient temperatures, inadequate thermal protection, or insufficient caloric intake. Studies have shown a relatively high incidence of neonatal hypothermia. For every 5 minutes of exposure to an environment below 36.5°C, the surface body temperature decreases by approximately 0.3°C.[2] Moreover, for each 1°C drop in body temperature, the mortality rate increases by 28%.[3] Severe hypothermia is a critical factor contributing to neonatal morbidity and mortality.[4,5] Preventing hypothermia

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during the first postnatal transfer is a crucial measure to reduce neonatal complications and improve outcomes. There are two key issues facing current clinical practice. Firstly, there is a lack of research on the risk factors related to the transportation of low body temperature in neonatal hospitals, which is mostly limited to the identification of a single risk factor. There is also a lack of systematic analysis of the interaction between multiple factors, and existing research generally has limitations such as small sample sizes and insufficient predictive power; Secondly, although some scholars have attempted to establish predictive models in recent years, few models have been constructed based on traditional statistical methods, failing to fully utilize the advantages of machine learning algorithms in processing high-dimensional and nonlinear clinical data, resulting in limited clinical applicability and prediction accuracy. Machine learning algorithms can extract disease-related features from a large amount of clinical data and construct predictive models to predict an individual's risk of disease occurrence.[6] Therefore, this study aims to address the issue of how to construct a neonatal in-hospital transport hypothermia prediction model with high predictive performance by integrating multidimensional clinical data and proposes the research hypothesis that "machine learning prediction models have better predictive performance than traditional models in neonatal in-hospital transport". We plan to analyze the incidence of neonatal in-hospital transport hypothermia and screen for related risk factors and use machine learning algorithms to establish and validate a population transport hypothermia prediction model, in order to provide an effective prediction method for reducing neonatal hypothermia during in-hospital transportation.

Materials and Methods

Study Population

This retrospective study included neonates born between January 2023 and June 2024 at a tertiary obstetrics and gynecology hospital in Shanghai who presented with high-risk factors. Inclusion criteria were as follows: neonates undergoing intra-hospital transfer within 2 hours after birth with complete clinical data and without withdrawal from the study. Exclusion criteria included transfer to a pediatric specialty hospital, missing post-transfer temperature monitoring results, or neonatal death. Neonates were categorized into a hypothermia group (Hypothermia), defined as a rectal temperature <36.5°C, and a normal temperature group (Control), defined as a rectal temperature between 36.5°C and 37.5°C. A total of 31 variables potentially influencing neonatal hypothermia were selected based on expert consensus and a review of the literature. Using the sample size calculation formula for multivariable binary prediction models,[7] the required sample size was determined to be 3,057 cases. This study was reviewed and approved by the Medical Ethics Committee of Obstetrics and Gynecology Hospital Affiliated to Tongji University (Ethics number: KS22362), and this study complies with the Helsinki Declaration.

Data Collection

Data were collected using paper-based medical record reporting forms. The information was sourced from the electronic medical record databases for mothers and neonates, as well as perinatal clinical nursing records. The data encompassed 20 neonatal variables (gender, gestational age, birth weight, birth 5-minute Apgar score, parity, touch after birth, wear hat, postnatal wipe, early breastfeeding, transfer incubator, quilt wrap, transit time, trachea cannula, Neonatal Asphyxia Resuscitation (NRP), asphyxia, oxygen intake, delayed cord ligation, shower after birth, and bathing time) and 12 maternal variables (age, delivery mode, education level, territory, standardized production inspection, prenatal hormone use, gestational hypertension, hypothermia, perinatal infection, delivery time, multiple gestation, and chorioamnionitis).

Statistical Methods

SPSS 26.0 and Python 3.6.9 software were used to analyze the data. All data have been tested for normality and conform to a normal distribution. The measurement data adopts t-test, expressed as mean ± standard deviation (($\overline{X} \pm S$)); The count data is expressed in frequency (percentage) [n (%)] using chi square test or Fisher's test. Use LASSO regression (Least Absolute Shrinkage and Selection Operator, LASSO) to screen for variables that are meaningful to the independent variable. Then, a random sampling method was used to select 60% of the cases as the Training cohort, 20% as the Test cohort, and 20% as the Validation cohort. Six machine learning algorithms, including Decision Tree (DT), Random

Forest (RF), eXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Naive Bayes Classifier (NB), were used to construct a prediction model, and a 10-fold cross validation method was applied to enhance the model's generalization ability. We then assessed the models' performance in the training and validation cohorts using the area under the receiver operator characteristic curve (AUC), accuracy, sensitivity, specificity F1 score and Brier score, and use SHAP values to explain the importance of optimal model feature variables.

Results

Univariate Analysis of Neonatal Intra-Hospital Transfer Hypothermia

A total of 10,342 neonates were transferred to the neonatal department in this study, of which 1282 were excluded due to incomplete temperature monitoring data, unclear medical history, or failure to meet inclusion/exclusion criteria. Ultimately, 9060 cases were included in the analysis, of which 5072 (55.98%) neonates experienced hypothermia during intra-hospital transfer.

There were statistically significant differences between the hypothermia group and the normal temperature group regarding 17 neonatal factors, including gestational age, birth weight, and birth 5-minute Apgar score ($P < 0.05$), as

Table 1 Comparison of Basic Neonatal Information Between Hypothermia and Normal Temperature Groups [n (%)]

Item	Hypothermia (n=5072)	Control (n=3988)	χ^2	*P*
Gender			10.864	0.001
Boy	2900 (57.18%)	2142 (53.71%)		
Girl	2172 (42.82%)	1846 (46.29%)		
Gestation (weeks)			892.427	<0.001
≥37	1232 (24.29%)	1978 (49.6%)		
32~<37	1770 (34.9%)	1374 (34.45%)		
28~<32	1462 (28.82%)	526 (13.19%)		
<28	608 (11.99%)	110 (2.76%)		
Weight (g)			822.535	<0.001
≥2500	1322 (26.06%)	1954 (49.00%)		
2000~2499	1498 (29.53%)	1250 (31.34%)		
1500~1999	1152 (22.71%)	572 (14.34%)		
<1500	1100 (21.69%)	212 (5.32%)		
Birth 5-minute Apgar score			15.625	<0.001
≥7	4164 (82.10%)	3398 (85.21%)		
<7	908 (19.70%)	590 (14.79%)		
Parity			4.443	0.035
Firstborn	2852 (56.23%)	2154 (54.01%)		
Non-firstborn	2220 (43.77%)	1834 (45.99%)		
Touch after birth			1612.829	<0.001
Yes	638 (12.58%)	2050 (51.40%)		
No	4434 (87.42%)	1938 (58.60%)		
Wear Hats			1151.521	<0.001
Yes	2110 (41.60%)	3076 (77.13%)		
No	2962 (58.40%)	912 (22.87%)		
Postnatal wipe			1086.361	<0.001
Yes	1818 (35.84%)	2820 (70.71%)		
No	3254 (64.16%)	1168 (29.29%)		
Early breastfeeding			120.776	<0.001
Yes	3458 (68.18%)	3132 (78.54%)		
No	1614 (31.82%)	856 (21.46%)		

(*Continued*)

Table 1 (Continued).

Item	Hypothermia (n=5072)	Control (n=3988)	χ^2	*P*
Transfer incubator			1137.158	<0.001
Yes	1340 (26.42%)	2458 (61.63%)		
No	3732 (73.58%)	1530 (38.27%)		
Quilt wrap			11.877	0.001
Yes	3766 (74.25%)	3086 (77.38%)		
No	1306 (25.75%)	902 (22.62%)		
Transit time (minute)			1.287	0.257
≥30	2140 (42.19%)	1730 (43.38%)		
<30	2932 (58.81%)	2258 (56.62%)		
Trachea cannula			264.033	<0.001
Yes	1264 (24.92%)	456 (11.43%)		
No	3808 (75.08%)	3532 (88.57%)		
NRP			907.967	<0.001
Yes	1650 (32.53%)	260 (6.52%)		
No	3422 (67.47%)	3728 (93.48%)		
Asphyxia			79.474	<0.001
Yes	1404 (27.68%)	782 (19.61%)		
No	3668 (72.32%)	3206 (80.39%)		
Oxygen intake			16.647	<0.001
Yes	1320 (26.03%)	890 (22.32%)		
No	3752 (73.97%)	3098 (77.68%)		
Delayed cord ligation			6.991	0.009
Yes	106 (2.09%)	118 (2.96%)		
No	4966 (97.91%)	3870 (97.04%)		
Shower after birth			1.283	0.266
Yes	4492 (88.56%)	3562 (89.32%)		
No	580 (11.44%)	426 (10.68%)		
Bath time(minute)			32.670	<0.001
<1	2534 (49.96%)	2224 (55.77%)		
1~2	1596 (31.47%)	1144 (28.69%)		
3~12	630 (12.42%)	428 (10.73%)		
>12	312 (6.15%)	192 (4.81%)		

Table 2 Comparison of Maternal Basic Information Between Hypothermia and Normal Temperature Groups [$(\overline{X} \pm S)$, n (%)]

Item	Hypothermia (n=5072)	Control (n=3988)	χ^2/t	*P*
Age (year)	29.96±6.10	30.77±6.42	−6.096*	0.001
Delivery mode			2.892	0.093
Eutocia	2978 (58.71%)	2412 (60.48%)		
Cesarean	2094 (41.29%)	1576 (39.52%)		
Educational Level			51.541	<0.001
High School and Below	1748 (34.46%)	1150 (28.84%)		
Bachelor's Degree	2804 (55.28%)	2274 (57.02%)		
Master's Degree and Above	520 (10.25%)	564 (14.14%)		
Territory			57.899	<0.001
Local	3494 (68.89%)	2442 (61.23%)		
Nonlocal	1578 (31.11%)	1546 (38.77%)		

(*Continued*)

Table 2 (Continued).

Item	Hypothermia (n=5072)	Control (n=3988)	χ^2/t	P
Standardized production inspection			1.141	0.294
Yes	4148 (81.78%)	3296 (82.65%)		
No	924 (18.22%)	692 (17.35%)		
Prenatal hormone use			10.593	0.001
Yes	3528 (69.56%)	2646 (66.35%)		
No	1544 (30.44%)	1342 (33.65%)		
Gestational hypertension			132.406	<0.001
Yes	1976 (38.96)	1094 (27.43%)		
No	3096 (61.04%)	2894 (72.57%)		
Hypothermia			18.301	<0.001
Yes	1596 (31.47%)	1090 (27.33%)		
No	3476 (68.53%)	2898 (72.67%)		
Perinatal infection			32.430	<0.001
Yes	1244 (24.53%)	778 (19.51%)		
No	3828 (75.47%)	3210 (80.49%)		
Delivery time			185.745	<0.001
8:00~16:00 (morning)	2446 (48.23%)	2496 (62.59%)		
16:00~8:00 (night)	2626 (51.77)	1492 (37.41%)		
Multiple pregnancy			295.954	<0.001
Yes	868 (17.11)	212 (5.32%)		
No	4204 (82.89%)	3776 (94.68%)		
Chorioamnionitis			103.502	<0.001
Yes	534 (10.53%)	716 (17.95%)		
No	4538 (89.47%)	3272 (82.05%)		

Note: *represents *t*-test.

detailed in Table 1. Additionally, significant differences were found between the two groups in 10 maternal factors, such as age, education level, and territory ($P < 0.05$), as detailed in Table 2.

Screening of Risk Factors for Neonatal Intra-Hospital Transfer Hypothermia

The variables with statistically significant differences in the univariate analysis were subjected to LASSO regression analysis. From the 27 variables, 10 significant risk factors were selected: Gestation, Weight, Touch after birth, Wear Hats, Postnatal wipe, Transfer incubator, Trachea cannula, Delivery time, Multiple pregnancy, and NRP. A 10-fold cross-validation method was used to validate the model with different combinations of variables. Based on the λ.1se variable selection criterion, the model with log(λ) = 0.027 showed excellent performance and was refined, as shown in Figure 1.

Construction of Risk Prediction Model Based on LASSO Regression

The variables selected by LASSO regression were imported as independent variables into the Python 3.6 environment. Using training set data, six machine learning algorithms (DT, RF, SVM, ANN, and NB) were used to construct prediction models for neonatal intra-hospital transfer hypothermia. Ten-fold cross-validation was performed for hyperparameter tuning and optimization, and the final model was determined after selecting the best hyperparameters.

Model Performance Evaluation

The performance of the six models in predicting neonatal intra-hospital transfer hypothermia was evaluated. All models demonstrated good stability, with no significant overfitting or underfitting observed. The results are shown in Table 3. Among the models, the RF model achieved the highest AUC values both on the training set (AUC = 0.987) and the validation set (AUC = 0.958), as shown in Figures 2 and 3. To assess the calibration of the models, calibration curves

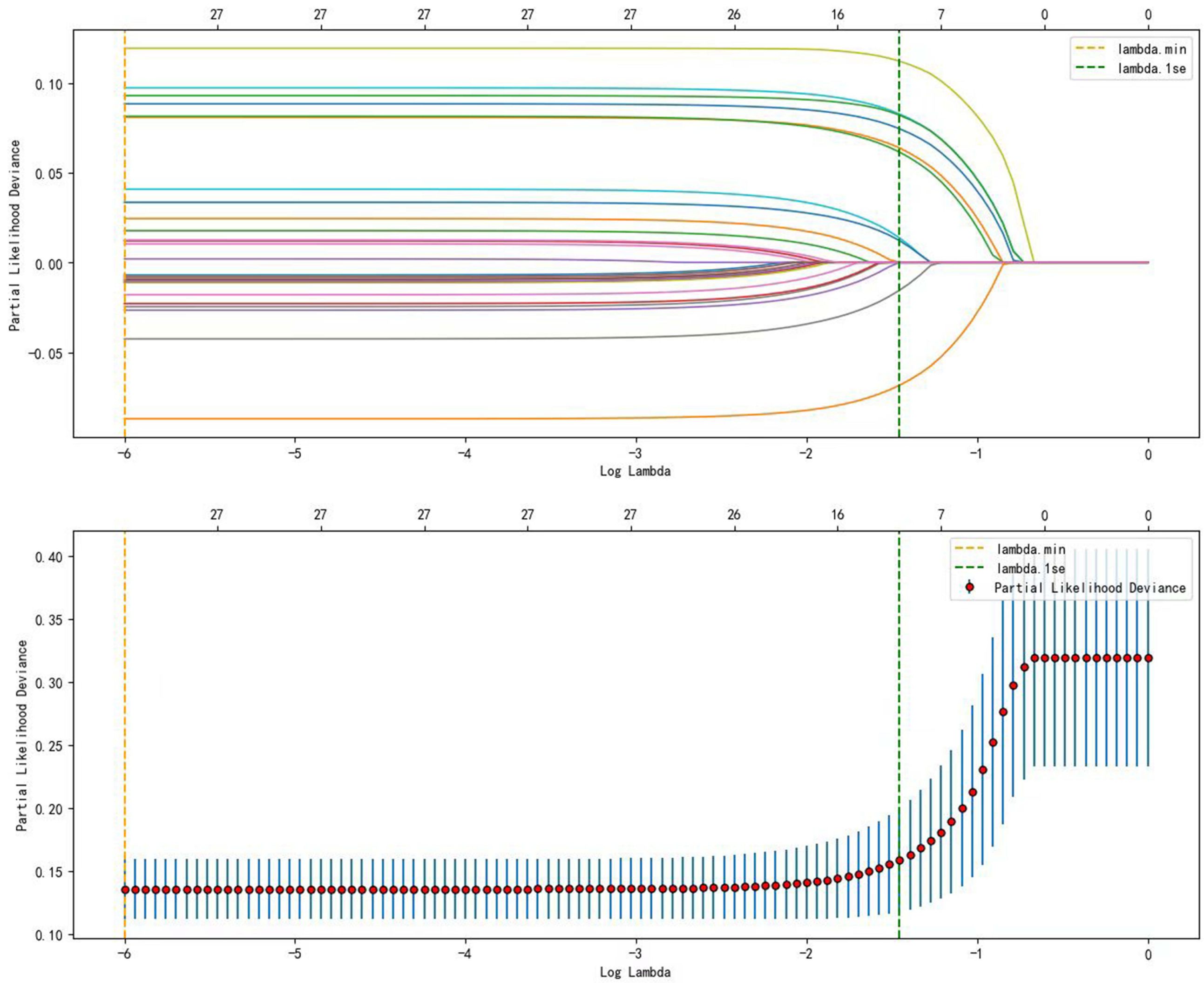

Figure 1 Hazard Factor Selection and Coefficient Distribution Plot Based on LASSO Regression.

were used to evaluate the consistency between predicted probabilities and actual occurrence probabilities, as shown in Figures 4 and 5.

SHAP Explanation for the Best Machine Learning Model

To further provide an intuitive understanding of how selected variables influence the RF model, SHAP was used for explanation, as shown in Figure 6. The results demonstrate that the SHAP summary plot ranks the importance of factors influencing neonatal intra-hospital transfer hypothermia as follows: Touch after birth, Wear Hats, Transfer incubator, Postnatal wipe, NRP, Weight, Gestation, Delivery time, Trachea cannula, and Multiple pregnancy, as presented in Figure 7.

Discussion

High Incidence of Neonatal Hypothermia During Intra-Hospital Transfer

The results of this study show that 55.98% of newborns transferred within the hospital between 2023 and 2024 exhibited signs of hypothermia. A study on in-hospital transportation of extremely low/ultra-low birth weight infants in 24 tertiary hospitals in Shandong Province, China, showed that 89.3% of the infants had hypothermia during transportation.[8] Yibelt et al[9] evaluated 117 transported newborns and found that the incidence of hypothermia after transportation was 65.8%. Fedine et al[10] retrospectively analyzed clinical data of 150 transported newborns and found that 39.3% of newborns had hypothermia

Table 3 Comparison of Evaluation Metrics for the 6 Machine Learning Models

Model	AUC	Accuracy	Sensitivity	Specificity	F1	Brier
Training cohort						
DT	0.946	0.937	0.948	0.939	0.945	0.053
RF	0.994	0.957	0.964	0.958	0.962	0.032
XGBoost	0.981	0.955	0.957	0.958	0.960	0.033
SVM	0.967	0.911	0.931	0.897	0.923	0.064
ANN	0.974	0.948	0.953	0.913	0.955	0.042
NB	0.967	0.824	0.847	0.816	0.846	0.141
Validation cohort						
DT	0.853	0.841	0.878	0.799	0.853	0.146
RF	0.962	0.889	0.918	0.856	0.897	0.077
XGBoost	0.953	0.881	0.891	0.870	0.888	0.079
SVM	0.942	0.861	0.898	0.829	0.872	0.093
ANN	0.937	0.860	0.882	0.836	0.870	0.102
NB	0.904	0.839	0.846	0.830	0.847	0.133

during hospitalization. Lee et al[11] study in Korea showed that the incidence of hypothermia in extremely premature infants was 74.1%. This study is lower than the above reports, possibly due to the large sample size of our study, which included a considerable number of full-term newborns rather than premature or low birth weight infants. In addition, the incidence of neonatal hypothermia reported by Demissie et al[12] was only 8.1%, which may be due to the relatively developed local

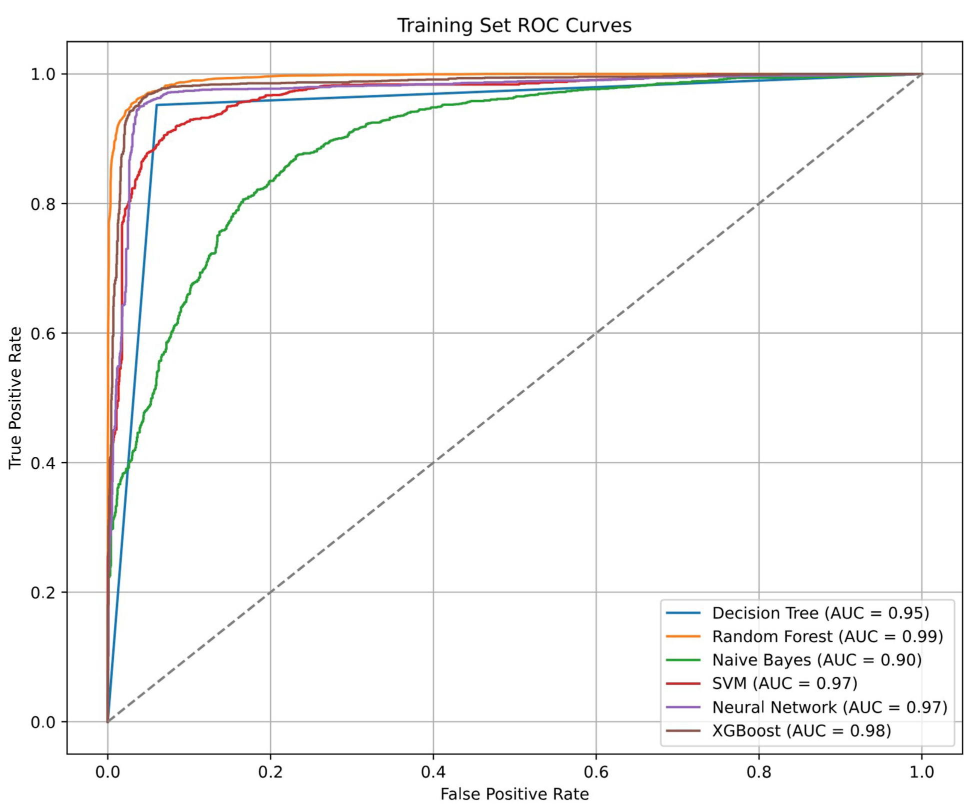

Figure 2 ROC Curves of 6 Machine Learning Models in Training Cohort.

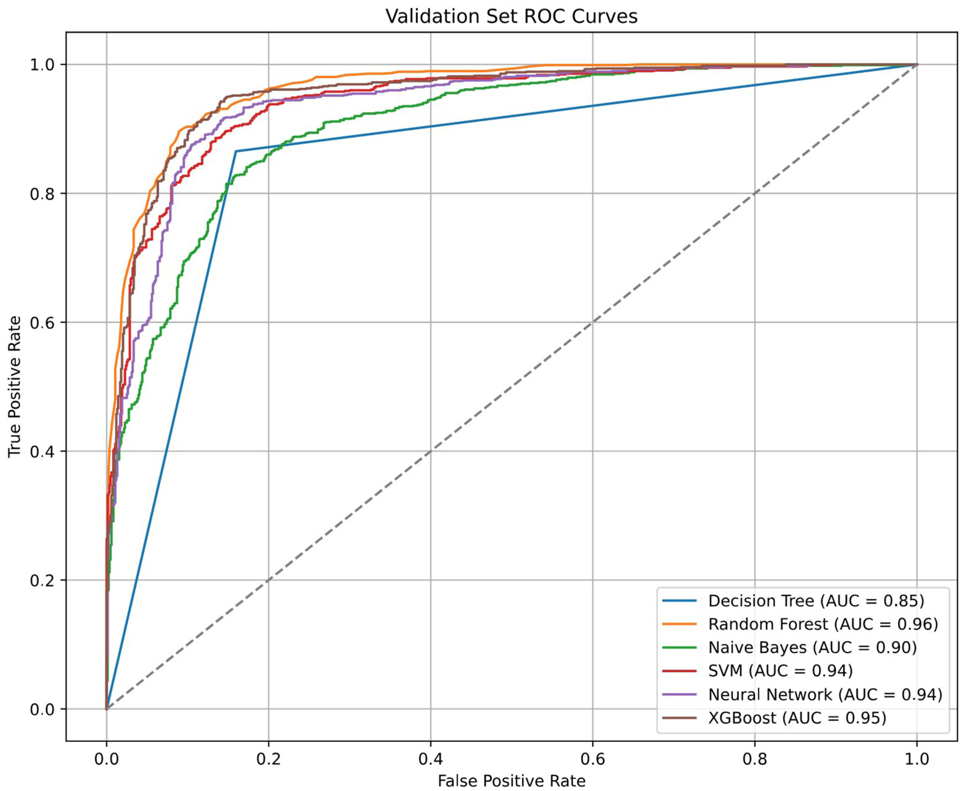

Figure 3 ROC Curves of 6 Machine Learning Models in Validation Cohort.

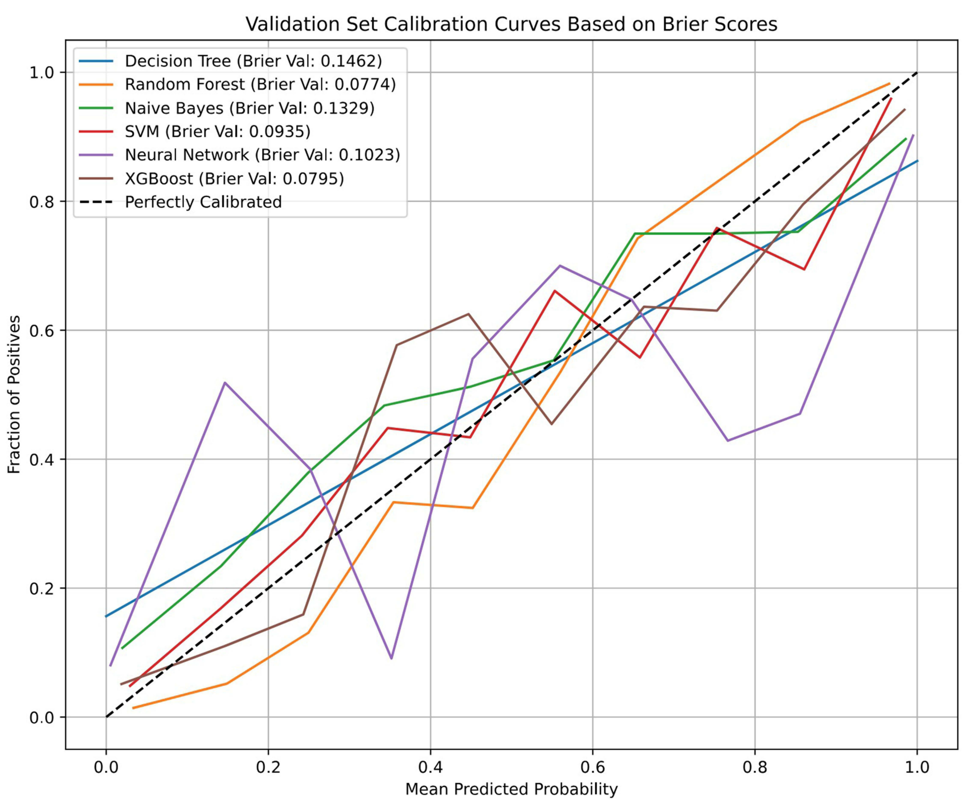

Figure 4 Calibration Curves of Six Machine Learning Models in Training Cohort.

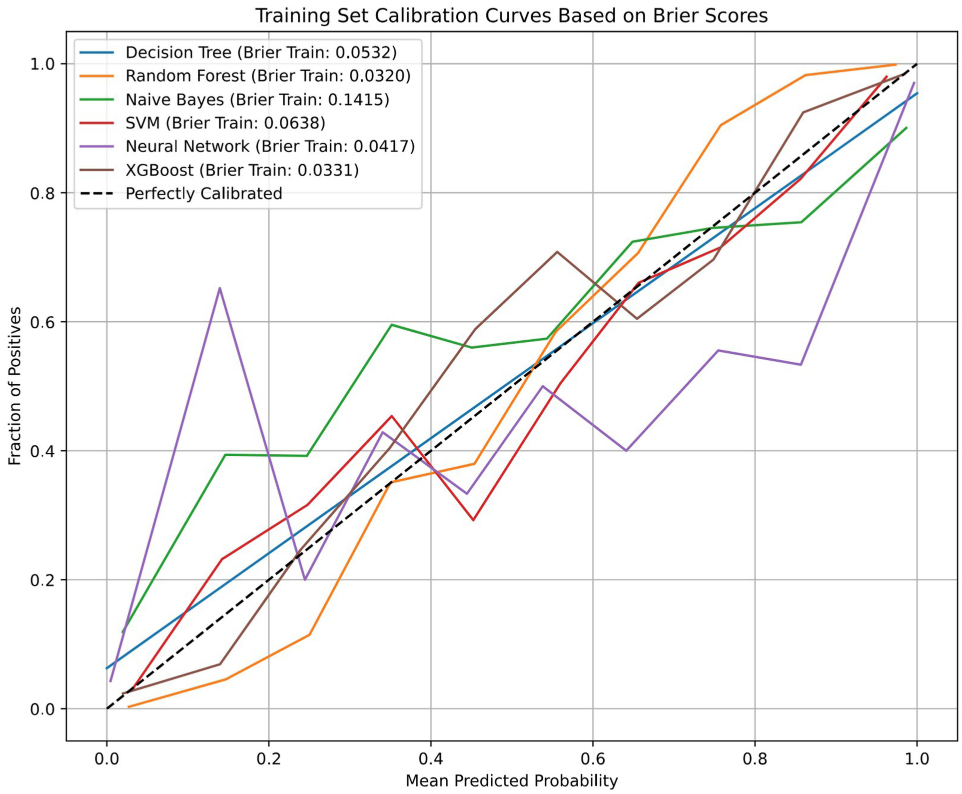

Figure 5 Calibration Curves of Six Machine Learning Models in Validation Cohort.

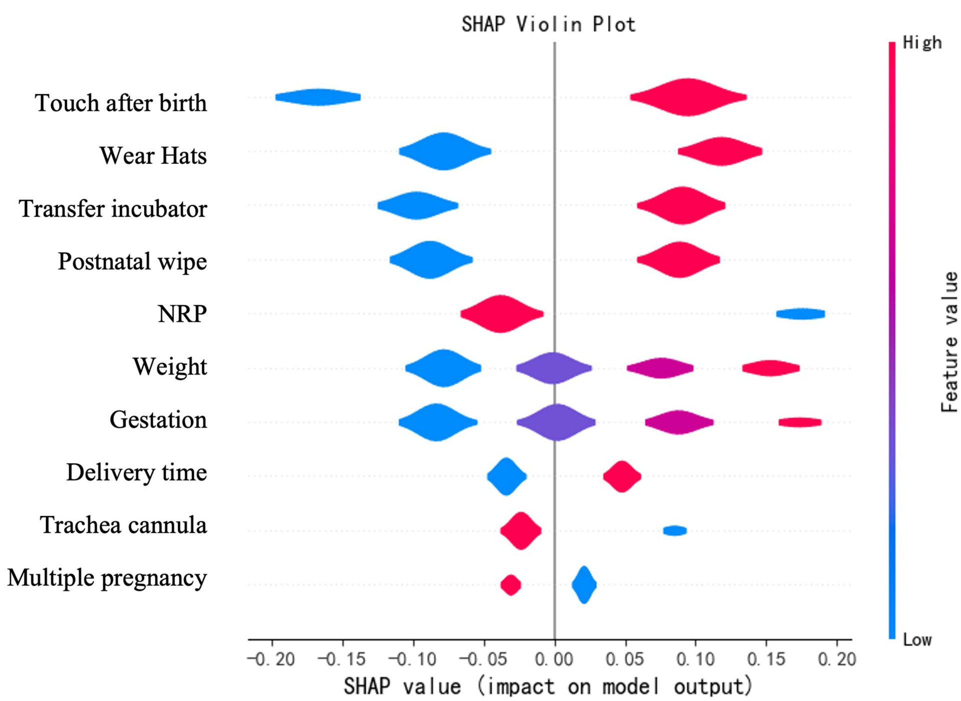

Figure 6 SHAP Summary of 10 Feature Variables in RF Model.

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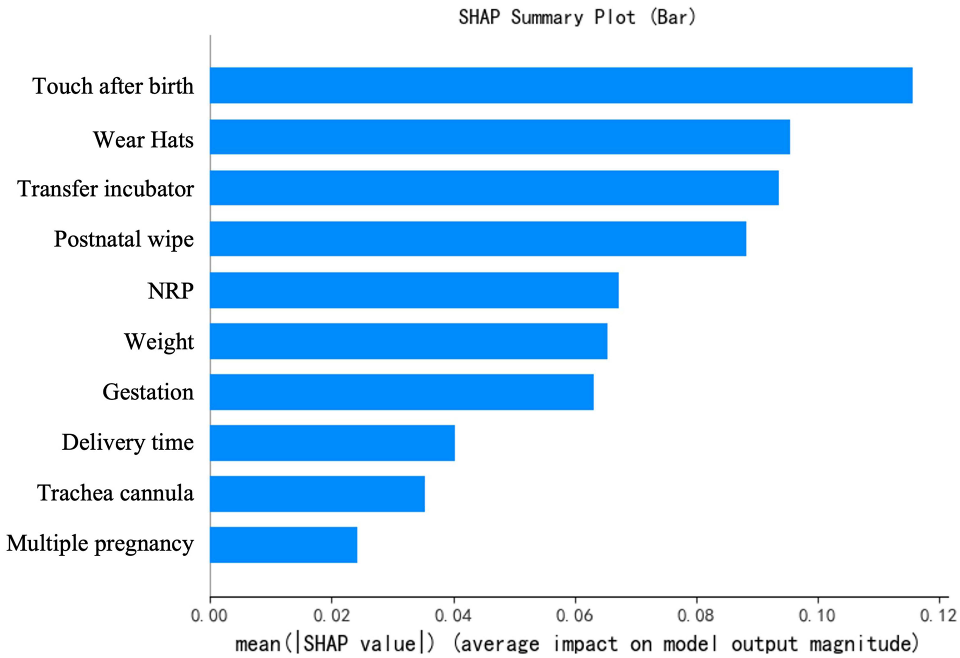

Figure 7 RF model variable importance ranking.

economy and early adoption of effective insulation measures (such as hot blanket wiping and wrapping), early breastfeeding, and effective physiological skin contact between mother and baby. In this study, the incidence of neonatal hypothermia was higher than in economically developed areas, and the overall incidence was higher. Considering that the reasons may be related to the lack of awareness of temperature management among medical staff, inadequate hospital technology and equipment, incomplete supervision mechanisms, inadequate implementation of warmth measures, lack of teamwork and insufficient data volume, it is necessary to strengthen the leadership construction of neonatal departments in the future, identify problems and obstacles encountered in the improvement process, negotiate with medical staff in various departments to solve problems, focus on the warmth quality of each premature infant, and improve overall compliance with measures.

Increased Risk of Hypothermia During Transfer for Preterm and Low Birth Weight Infants

The results of the univariate analysis indicate that the incidence of hypothermia is closely related to the neonatal gestational age and birth weight ($P<0.01$), meaning that preterm and low birth weight infants are at a higher risk of developing hypothermia during intra-hospital transfer. This finding is consistent with previous studies.[13] Additionally, gestational age and birth weight were identified as significant influencing factors in the importance ranking of the best model. The risk of hypothermia during transfer for extremely preterm infants is 6.908 times higher than that for full-term infants, and the risk for very low birth weight infants is 7.252 times higher than that for normal weight infants. The possible reasons for this heightened risk include insufficient brown adipose tissue and thinner skin in preterm and low birth weight infants, which leads to greater heat loss through radiation. Furthermore, these infants lack an effective thermoregulatory mechanism, such as shivering, and have insufficient glycogen reserves to combat hypothermia. Alebachew et al[1] reported that the likelihood of hypothermia in preterm infants is about 3.4 times higher than that in full-term infants. The higher incidence of hypothermia observed in our study compared to this report may be attributed to differences in neonatal temperature management and birth rates across the studies. Phoya et al[14] confirmed that the incidence of hypothermia during transfer is significantly correlated with the mortality rate in preterm infants. Combining the results of these studies, it is evident that implementing necessary measures to prevent hypothermia in preterm and low birth weight infants during the immediate post-birth and transfer periods is crucial.

Analysis of Operational Measures to Reduce Neonatal Hypothermia During Intra-Hospital Transfer

The World Health Organization's guidelines on neonatal temperature management emphasize that newborns can be prevented from losing heat through timely wiping, early breastfeeding, delayed bathing, effective tactile stimulation (kangaroo care), and thermal protection during transfer.[15] Our model also identified that tactile stimulation after birth, wiping, wearing hats, and transferring in an incubator were effective measures to reduce the incidence of hypothermia during transfer. Newborns have a relatively large head-to-body ratio, and their skull sutures and fontanelles remain open, making them prone to heat loss. Therefore, newborns who do not wear hats are more likely to experience hypothermia than those who do. The mechanism by which effective tactile stimulation reduces hypothermia is related to heat conduction due to skin contact, as well as the stimulation of the newborn's breathing by the caregiver's chest and abdominal movements, which increases heat production through oxidative phosphorylation.[16] The univariate analysis also showed that early breastfeeding and the duration of neonatal bathing were associated with the occurrence of hypothermia during transfer. Mukunya et al[17] found that newborns who were not breastfed early were more likely to experience hypothermia. The potential explanation for this is that early breastfeeding facilitates effective contact between the mother and infant, reducing heat loss, while providing high-quality protein that helps maintain nitrogen balance and energy metabolism. The practice of bathing newborns shortly after birth remains controversial. Some studies suggest that bathing immediately after birth can lead to a drop in body temperature, and it is recommended that bathing be avoided within the first 24 hours of life.[18] Therefore, it is advisable to implement skill training and effective thermal protection measures, such as appropriate water temperature, skin-to-skin contact between the mother and infant, and the use of warm towels for wiping to prevent heat loss in newborns.

Analysis of Non-Operational Measures to Reduce Neonatal In-Hospital Transfer Hypothermia

In our model, the timing of delivery was identified as a risk factor for neonatal hypothermia during in-hospital transfer. This may be related to factors such as the temperature differences between day and night, as well as insufficient staffing. It is important to emphasize that even when the environmental temperature is higher, the risk of hypothermia in preterm infants should not be underestimated. The best evidence summary of prevention and management of neonatal hypothermia in China shows that[19] although neonates born in cold seasons had a higher probability of hypothermia, low-birth-weight infants born in warm seasons were five times more likely to experience hypothermia than those born in cold seasons. This difference may be due to the reduced awareness of healthcare workers about the risk of hypothermia in low-birth-weight infants in warmer seasons. Additionally, neonates with cardiac and pulmonary insufficiency (such as those with a history of resuscitation, intubation, or asphyxia) were found to have a higher incidence of hypothermia during in-hospital transfer compared to other neonates. The possible reasons for this include the tendency for hypoglycemia due to the inability to initiate early breastfeeding, as well as inadequate oxygen uptake and utilization, leading to insufficient thermogenesis. These findings are consistent with the results of Phoya et al.[14] Furthermore, this study also identified multiple pregnancies as a risk factor for neonatal hypothermia, possibly due to the higher proportion of preterm and low-birth-weight infants among multiple births.

Advantages of the Neonatal In-Hospital Transfer Hypothermia Model

This study used LASSO regression to select 10 feature variables, significantly reducing multicollinearity between the variables. Six machine learning algorithms were then used to construct and compare prediction models. The models were evaluated based on accuracy, sensitivity, specificity, F1 score, Brier score, ROC curves, and calibration curves. The results showed that the RF model had the highest AUC values in both the training set (AUC = 0.994) and the validation set (AUC = 0.962). It also had the best overall performance across all evaluation metrics. Additionally, the calibration curve confirmed that the RF model demonstrated higher predictive accuracy in the validation set. Although the specificity of the RF model was slightly lower than that of the XGBoost model in the validation set, this difference may be attributed to the smaller sample size included in the validation set. Therefore, this study identified the RF model as the optimal model for predicting neonatal hypothermia during in-hospital transfer. The RF model has strong adaptability to the dataset, allowing all data to be utilized for model construction and validation, effectively preventing overfitting. As a result, the RF model exhibited the best overall predictive performance in the test set. Although LASSO regression was used to select feature variables, it only reflects the overall impact of the variables and cannot capture the effect of variables within specific categories. To address this limitation, we introduced the SHAP method to interpret the importance and contribution of each variable in the RF model. In clinical practice, this model can assist pediatric clinicians in identifying neonates at high risk for hypothermia during transfer, allowing them to implement effective preventive measures, reduce the incidence of hypothermia, and improve neonatal outcomes. Healthcare providers can also print SHAP plots on paper or use a web-based calculator for risk assessment of neonatal hypothermia during transfer.

Limitations of the Study

This study did not obtain data on the temperature of the delivery room or operating room, maternal temperature, or kangaroo care, which may be attributed to incomplete or missing medical history and the limited implementation of these practices. Previous studies have shown that the temperature in the operating room can affect both maternal and neonatal body temperatures.[20] Additionally, kangaroo care has been proven to be beneficial for managing the body temperature of preterm infants.[21] Therefore, it cannot be ruled out that these factors may have contributed to neonatal transport hypothermia.

Conclusion

In this study, the incidence of neonatal hypothermia following in-hospital transport was found to be relatively high. Ten feature variables selected by LASSO regression, including preterm birth, low birth weight, post-birth contact, use of hats, drying, presence of cardiopulmonary dysfunction, multiple pregnancies, and delivery time, showed good predictive value for neonatal hypothermia during in-hospital transport. Furthermore, among the six machine learning models built based on these ten feature variables, the RF model demonstrated the best overall predictive ability for neonatal hypothermia during in-hospital transport, making it a promising tool for clinical application.

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Disclosure

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