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ORIGINAL RESEARCH

Performance of Machine Learning Algorithms in Predicting Prolonged Mechanical Ventilation in Patients with Blunt Chest Trauma

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Purpose: Mechanical ventilation (MV) is one of the most common treatments for patients with blunt chest trauma (BCT) admitted to the intensive care unit (ICU). Our study aimed to investigate the performance of machine learning algorithms in predicting the prolonged duration of mechanical ventilation (PDMV) in patients with BCT.

Methods: In this single-center observational study, patients with BCT who were treated with MV through nasal or oral intubation were selected. PDMV was defined as the duration of mechanical ventilation ≥7 days after endotracheal intubation (normal vs prolonged MV; dichotomous outcomes). K-means was used to cluster data from the original cohort by an unsupervised learning method. Multiple machine learning algorithms were used to predict DMV categories. The most significant predictors were identified by feature importance analysis. Finally, a decision tree based on the chi-square automatic interaction detection (CHAID) algorithm was developed to study the cutoff points of predictors in clinical decision-making.

Results: A total of 426 patients and 35 characteristics were included. K-means clustering divided the cohort into two clusters (high risk and low risk). The area under the curve (AUC) of the DMV classification algorithms ranged from 0.753 to 0.923. The importance analysis showed that the volume of pulmonary contusion (VPC) was the most important feature to predict DMV. The prediction accuracy of the decision tree based on CHAID reached 86.4%.

Conclusion: Machine learning algorithms can predict PDMV in patients with BCT. Therefore, limited medical resources can be more appropriately allocated to BCT patients at risk for PDMV.

Keywords: mechanical ventilation, blunt chest trauma, machine learning, pulmonary contusion

Introduction

Chest trauma is a serious threat to human health, accounting for approximately 60% of all patients with multiple injuries, among which blunt injuries account for approximately 70%, with an in-hospital mortality can reach 20%-25%.[1–4] Invasive mechanical ventilation (MV) is often required for patients admitted to the intensive care unit (ICU) for hypoxemia due to blunt chest trauma (BCT) and pulmonary contusion (PC).[5–7] Theoretically, after MV, the oxygenation of BCT patients improves, and the ventilator can be successfully removed after a short time. However, there are still quite a few BCT patients with prolonged duration of mechanical ventilation (PDMV).[8,9] Multiple studies have shown that, compared with the normal duration of mechanical ventilation (NPMV), patients with PDMV had higher chronic and acute disease burdens, higher incidences of hospital-acquired complications (sepsis and ventilator-associated pneumonia), and lower clinical and economic outcomes (in-hospital

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mortality, medical costs).[10–14] Therefore, we need to accurately identify risk factors for PDMV to shorten DMV and prevent unnecessary prolongation.

A prospective study of 69 patients with BCT showed that age, bilateral thoracic injury and severe cranial trauma were independent predictors of PDMV.[15] However, the study also included other non-chest injuries. Therefore, these findings cannot be extrapolated to isolated patients with chest trauma. Schieren et al[16] also found that BCT combined with traumatic cranial injury (TBI) significantly prolonged DMV and was associated with higher mortality. In addition, the body mass index (BMI) and trauma severity score were also identified as risk factors for PDMV in BCT patients.[17,18] Additional studies have shown that intrathoracic injury is the main risk factor for PDMV, including flail chest, acute respiratory distress syndrome and pulmonary contusion.[19–21] However, a portable tool that can accurately predict the occurrence of PDMV in BCT patients is still lacking.

Predictive analysis and machine learning have become reliable prognostic tools for patients based on relevant characteristic variables.[22] The development of a prediction model centered on patient outcome variables can help clinicians and medical decision makers improve the rational utilization of social medical resources and better coordinate the allocation of medical resources based on different treatment plans.[23]

Given the adverse outcomes of PDMV in BCT patients, we hypothesized that algorithms based on multiple machine learning could accurately predict whether BCT patients would undergo normal or prolonged DMV. Next, we aimed to find the most relevant characteristic variables that were capable of solving the classification task.

Methods

Batch Evaluation and Ethical Issues

This was a single-center observational study of patients admitted to the emergency department and ICU of Affiliated hospital of Yangzhou University between August 2017 and October 2022 for MV for BCT. We obtained a patient clinical cohort from the emergency information system and the inpatient electronic case system and masked the true information of all enrolled patients. The primary inclusion criteria included patients with BCT who received MV during the relevant time period. Exclusion criteria included the following: age < 18 years; sudden cardiac and respiratory arrest after admission; length of hospital stay < 48 hours; MV due to other reasons; repeated admissions for chest trauma; and incomplete medical history. The study was approved by the ethics committees of Affiliated hospital of Yangzhou University and complied with the Declaration of Helsinki. Due to the observational nature of the study, written informed consent was waived for all enrolled patients.

Parameters Used and Definition

All included variables are shown in Table 1. The demographic cohort and underlying diseases of all subjects were recorded to include patient histories 3 months before injury; disease severity scores, concomitant injuries, laboratory cohort (except for C-reactive protein), fluid resuscitation, procedures, and surgery were collected within 24 hours after injury. Biological samples, including hemoglobin, blood lactate, and CRP (48 hours after admission), were collected from the patient's venous blood using an appropriate blood collection tube, such as an ethylenediaminetetraacetic acid (EDTA) anticoagulant tube or a vacuum blood collection tube, to prevent hemolysis during the collection process. All classification features were divided into three categories at most, and the classification variables were represented in a binary form (assigned "1" if the feature existed and "0" if it did not).

DMV was defined as the duration from the start of ventilation to the first successful extubation. DMV≥7 days was considered to be PDMV, whereas a duration of less than 7 days was considered to be NDMV.[24,25] We process the missing data for the cohort according to missing mechanisms. Missing values for <10% of the features were estimated and used as input features in cluster analysis. Features with missing values between 10–30% were not used as clustering input features. Finally, the features were excluded if the missing values were >30%. We used the random forest multiple filling method to fill in the missing values of the features.

Table 1 Comparisons of the Features Were Obtained Through the K-Means Cluster Analysis, Including the Continuous Scale Feature Duration of Mechanical Ventilation

Features	All (n=426)	Clusters		*P*-Value
		High Risk (n=106)	Low Risk (n=320)	
Age, years,(mean±SD)	41.6±14.0	58.2±8.1	34.4±8.9	<0.001
Male sex, n (%)	209(49.1)	58(54.7)	151(47.2)	0.188
BMI, kg m^{-2}, (mean±SD)	21.0±4.1	23.9±4.6	19.8±3.2	<0.001
GCS score, point, median (IQR)	8(3–15)	6(4–12)	8(6–15)	0.015
ISS score, point, (mean±SD)	39.0±8.4	40.6±8.1	38.4±8.5	0.011
Chronic pulmonary disease, n (%)	58(13.6)	19(17.9)	39(12.2)	0.659
Three-dimensional reconstruction of chest images, median (IQR)				
Volume of pulmonary contusion	13.2(11.4–38.6)	22.1(14.7–29.6)	12.3(9.8–14.7)	<0.001
Number of ribs fractured	7(4–10)	8(5–10)	6(4–7)	0.017
Chronic cardiac failure, n (%)	45(10.6)	16(15.1)	29(9.0)	0.416
Associated injury types, n (%)				
Traumatic brain injury	54(12.7)	19(17.9)	35(3.9)	0.401
Sternum fractures	131(3.4)	37(34.9)	94(29.4)	0.542
Flail chest	94(5.1)	38(35.8)	56(17.5)	0.055
Spine fractures	33(9.7)	10(9.4)	23(7.2)	0.998
Maxillofacial fractures	46(11.9)	16(15.1)	30(9.3)	0.482
Complications, n (%)				
Hemothorax	185(39.8)	60(56.6)	125(39.1)	0.290
Pneumothorax	244(57.3)	75(70.8)	169(52.8)	0.813
Ventilator associated pneumonia	56(13.1)	22(20.8)	34(10.6)	0.116
Acute respiratory distress syndrome	124(29.1)	44(41.5)	80(25.0)	0.134
Laboratory value (initial value), median (IQR)				
Hemoglobin, g dL^{-1}	8 (6.5–11.9)	8 (6.9–11.4)	9 (7.9–11.6)	0.325
CRP 48h after admission, mg/L	14.7(10.9–21.6)	21.6(12.6–32.6)	14.3(10.9–18.6)	<0.001
Blood lactate, mmol L^{-1}	3.7(3.0–4.3)	3.5(3.0–4.1)	3.7(3.2–4.3)	0.705
Medical treatment, median (IQR)				
DMV, day	7(2–11)	10(8–11)	4(2–7)	<0.001
Fluid infusion within 24 hours of admission, median (IQR)				
RBC, mL	1150(650–1750)	1050(650–1650)	1350(750–1750)	0.629
Plasma, mL	920(570–1180)	910(580–1150)	965(750–1020)	0.064
Platelets, units	1(0–2)	1(0–2)	2(0–2)	0.083
All fluid infusion	5250(4100–7355)	5155(4150–7200)	5500(4250–7290)	0.504
Operations, n (%)				
Surgery on limbs and joints	18(4.2)	8(7.5)	10(3.1)	0.181
Surgery on pelvic	110(25.8)	35(33.0)	75(23.4)	0.684
Surgery on abdominal	7(1.6)	3(2.8)	4(1.3)	0.465
Surgery on thorax	15(3.5)	6(5.7)	9(2.8)	0.460
Surgery on brain	112(26.3)	39(36.8)	73(22.8)	0.211
Surgery on spine	21(4.9)	8(7.5)	13(4.1)	0.074
Thoracic close drainage	19(4.4)	7(6.6)	12(3.8)	0.810
Transcutaneous tracheostomy	101(23.7)	38(35.8)	63(19.7)	0.066

Abbreviations: IQR, interquartile range; BMI, body mass index; GCS, glasgow coma scale; ISS, injury severity score; CRP, C-reactive protein; DMV, duration of mechanical ventilation; RBC, red blood cell.

Statistical Processing

We conducted unsupervised learning of the baseline cohort through the K-means algorithm, evaluated whether cluster analysis could be performed according to the characteristics of the cohort set, and then automatically determined the optimal number of clusters according to Schwarz's Bayesian Criterion (BIC) (Figure 1).

The Mann–Whitney *U*-test or chi-square test was used to compare significant differences among cluster variables. A decision tree with the CHAID algorithm was used to determine the discrepancy between the child node and the parent node. The discrepancy between the observed count and the expected count of the objective variable for each node and the summation of the squares of these normalized discrepancies was used as the chi-square value. The CHAID algorithm was applied for cross verification (n = 5). The maximum tree depth was 3, the minimum number of parent nodes was 10, and the minimum number of child nodes was 5. Therefore, 14 nodes were obtained, 8 terminal nodes were obtained, and the depth was 3. The missing values of continuous variables were replaced by linear regression, and the missing values of classified variables were interpolated by logistic regression.

Finally, we applied multiple machine learning and deep learning algorithms to predict the classification of the target DMV, including the random forest classifier, logistic regression, K-nearest neighbor, decision tree classifier, Gaussian naive Bayes (Gauss NB), stochastic gradient descent (SGD) classifier, support vector machine (SVM), convolutional neural network (CNN), radial basis function neural network (RBNN), and multilayer perception (MLP).

Computer hardware and software environment specifications were as follows: Central Processing Unit: Advanced Micro Devices Ryzen 5 3500Ux64-Core Processor (Santa Clara, CA, USA); Random Access Memory: 16 GB; Graphics Processing Unit: Radeon Vega Mobile Gfx 2.10 GHz (Santa Clara, CA, USA); Python version: 3.10.4 (64-bit) (Wilmington, DE, USA); Operating System: Windows 10 (Redmond, WA, USA). Statistical analyses were conducted in Python and Stata SE v16.0 (IBM, Armonk, NY, USA).

Result

The K-means algorithm was used for a secondary cluster analysis, and the original cohort set was divided into two clusters, including a high-risk group and a low-risk group. In addition, we evaluated which features were vital for the cluster analysis. We used the DMV (continuous variable) in the original cohort for the first cluster analysis, resulting in two clusters, which included 320 cases (75.1%) in the high-risk group and 106 cases (24.9%) in the low-risk group (Figure 2). The cohort distribution showed that all high-risk cluster variables (DMV, VPC, BMI, CRP, GCS score, ISS score, and number of rib fractures 48 hours after admission) were significantly higher than those in the low-risk group,

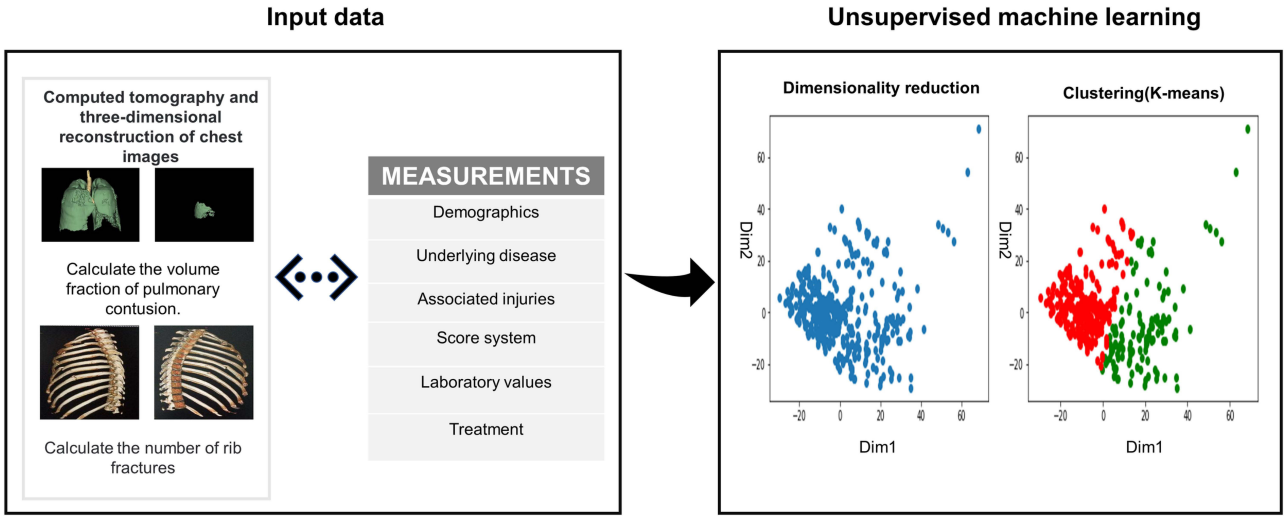

Figure 1 Flow chart of K-means cluster analysis. Input data consist of both complex descriptors from Chest imaging data (eg 3-D reconstruction of chest CT images of a 58-year-old male patient showing the VPC. The VPC =285.34cm3 /2627.05cm3 *100%=10.9%; the number of rib fractures=8) and clinical parameters (left pane), which are used by the unsupervised machine learning algorithm classify data through dimensionality reduction (right pane).

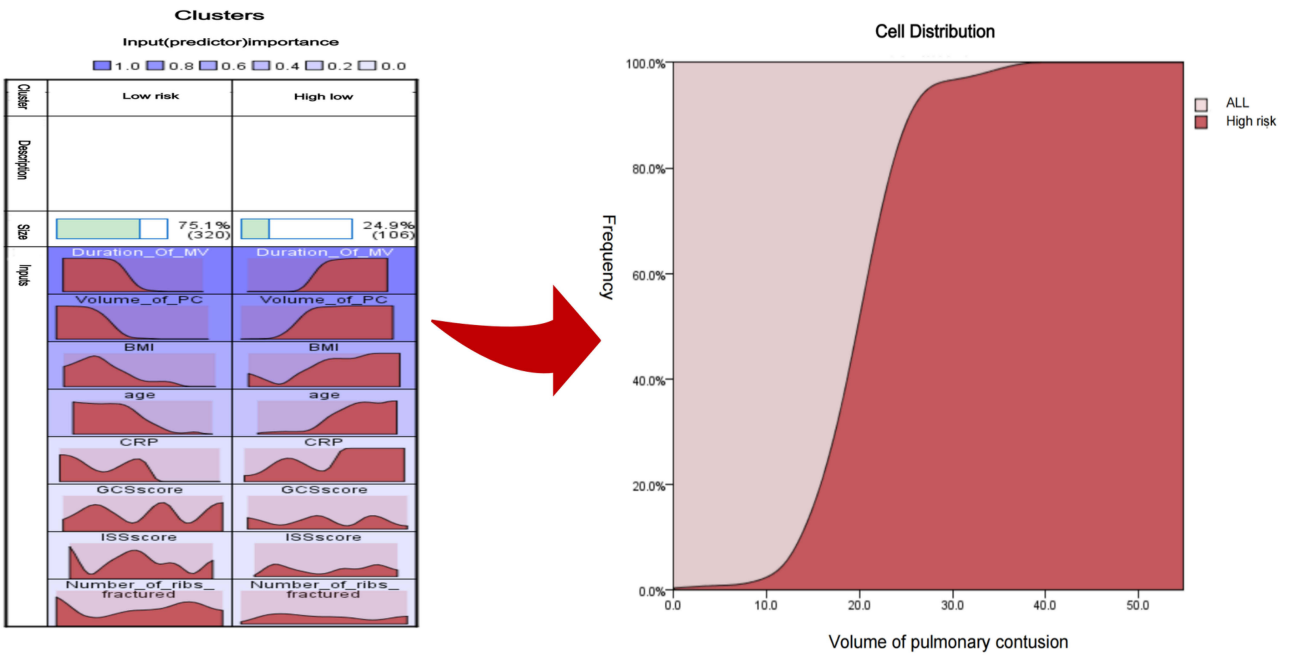

Figure 2 K-means cluster analysis for the raw DMV target variable (continuous scale). The most important feature to classify the data was the VPC, followed by the BMI, age, CRP, GCS, ISS, and number of ribs fractured excluding the DMV. The distribution charts show the distribution of the features for both clusters. An example feature (VPC) is shown to help interpretation. The selected feature shows that the distribution of VPC is right-shifted for the high risk cluster, whereas it is left-shifted for the low risk cluster.

P<0.05 (Table 1). Thus, these two clusters may represent the degree of DMV risk in patients (the high-risk group showed higher VPC, BMI, CRP 48 hours after admission, ISS score, and number of rib fractures; and lower GCS scores).

The DMV (dichotomous variable) was used as the cohort type in the second cluster analysis, and two clusters were also obtained, including 319 cases (74.9%) in the high-risk group and 107 cases (25.1%) in the low-risk group (Figure 3). The results showed that the cluster variables (DMV, VPC, BMI, CRP, ISS score and number of rib fractures

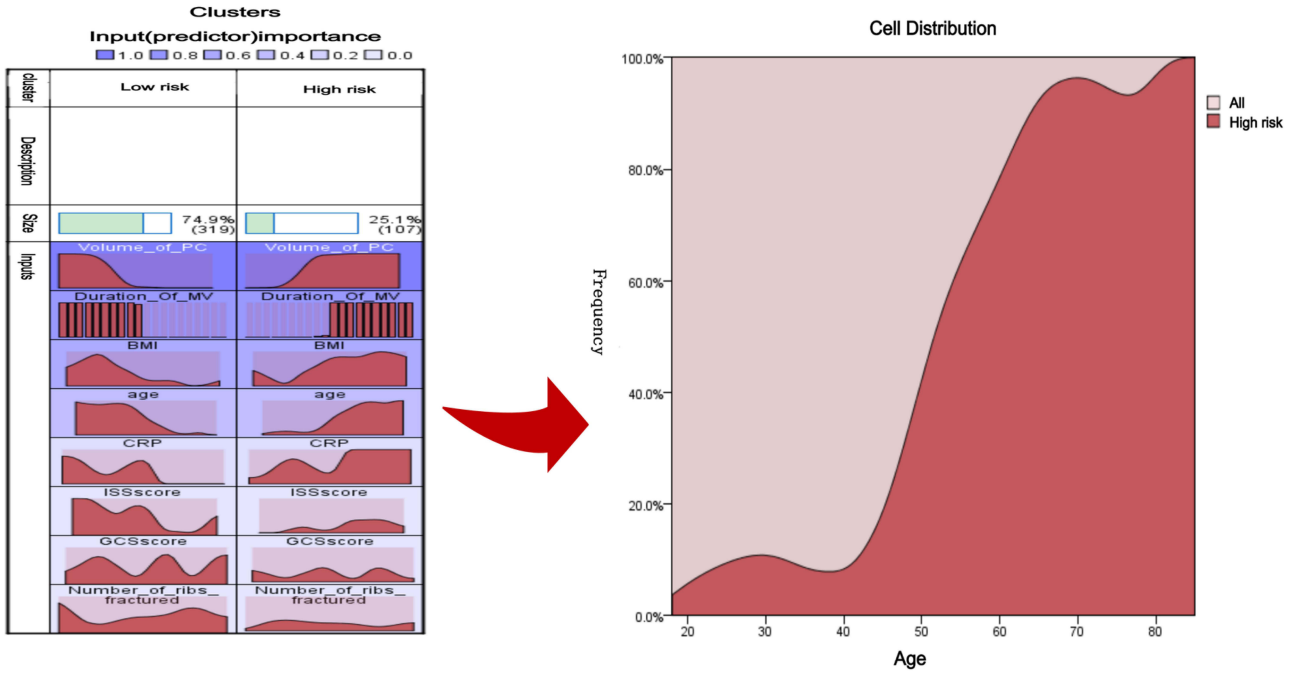

Figure 3 K-means cluster analysis for the binary DMV class (prolonged versus normal).The most important feature to classify the data was the VPC, followed by DMV class, BMI, age, CRP, ISS score, GCS score and number of ribs fractured.The distribution charts show the distribution of the features for both clusters. An example feature (age) is shown to help interpretation. The selected feature shows that age distribution is right-shifted for the high risk cluster (including the DMVclass), whereas it is left-shifted for the low risk cluster.

at 48 hours after admission) in the high-risk group were significantly higher than those in the low-risk group, except for the GCS score, P< 0.05 (Table 2). In addition, the distribution of DMV was significantly different between the high-risk group and the low-risk group, with all PDMV cases in the high-risk group and NDMV in the high-risk group, p < 0.001.

Multiple machine learning algorithms were used to predict the classification of DMV, among which the AUC of the MLP model reached a maximum of 0.923 (Figure 4). The feature importance analysis showed that VPC was a vital

Table 2 Comparisons of the Features Were Obtained Through the K-Means Cluster Analysis, Including the Binary Class Feature of Duration of Mechanical Ventilation

Features	All (n=426)	Clusters		*P*-Value
		High Risk (n=107)	Low Risk (n=319)	
Age, years,(mean±SD)	40.8±13.8	58.1±8.3	35.6±8.6	<0.001
Male sex, n (%)	209(49.5)	57(53.8)	152(47.6)	0.175
BMI, kg m^{-2}, (mean±SD)	20.9±3.9	24.1±4.8	19.6±3.7	<0.001
GCS score, point, median (IQR)	8(5–15)	6(5–14)	9(5–15)	0.020
ISS score, point, (mean±SD)	38.8±8.2	40.2±7.9	38.0±8.1	0.014
Chronic pulmonary disease, n (%)	58(13.1)	17(15.8)	51(15.9)	0.559
Three-dimensional reconstruction of chest images, median (IQR)				
Volume of pulmonary contusion	134(11.6–38.7)	22.2(14.8–29.8)	12.5(9.9–14.9)	<0.001
Number of ribs fractured	7(4–11)	9(5–11)	6(3–8)	0.012
Chronic cardiac failure, n (%)	45(10.6)	15(14.0)	30(9.4)	0.409
Associated injury types, n (%)				
Traumatic brain injury	54(12.7)	19(17.7)	35(11.0)	0.386
Sternum fractures	131(3.4)	37(34.5)	94(29.5)	0.512
Flail chest	94(5.1)	38(35.5)	56(17.6)	0.058
Spine fractures	33(9.7)	10(9.3)	23(7.2)	0.813
Maxillofacial fractures	46(11.9)	16(15.0)	30(9.4)	0.428
Complications, n (%)				
Hemothorax	185(39.8)	59(55.1)	126(39.5)	0.175
Pneumothorax	244(57.3)	72(67.3)	172(53.9)	0.721
Ventilator associated pneumonia	56(13.1)	24(22.4)	32(10.0)	0.108
Acute respiratory distress syndrome	124(29.1)	48(44.9)	76(23.8)	0.127
Laboratory value (initial value), median (IQR)				
Hemoglobin, g dL^{-1}	8 (6.4–11.8)	8 (6.8–11.7)	9 (7.8–11.5)	0.256
CRP 48h after admission, mg/L	14.6(10.8–21.4)	21.5(12.3–32.7)	14.3(11.0–17.4)	<0.001
Blood lactate, mmol L^{-1}	3.6(3.1–4.2)	3.4(3.1–4.2)	3.5(3.1–4.0)	0.607
Medical treatment, median (IQR)				
DMV, n%	426(100)	107(100)	319(100)	<0.001
Fluid infusion within 24 hours of admission, median (IQR)				
RBC, mL	1150(650–1750)	1150(645–1750)	1450(850–1650)	0.549
Plasma, mL	915(565–1080)	905(576–1250)	970(750–1120)	0.075
Platelets, units	1(0–2)	1(0–2)	2(0–2)	0.073
All fluid infusion	5350(4800–7055)	5255(4550–7300)	5550(4350–7300)	0.544

(*Continued*)

Table 2 (Continued).

Features	All (n=426)	Clusters		*P*-Value
		High Risk (n=107)	Low Risk (n=319)	
Operations, n (%)				
Surgery on limbs and joints	18(4.2)	7(6.5)	11(3.4)	0.143
Surgery on pelvic	110(25.8)	34(31.8)	70(21.9)	0.664
Surgery on abdominal	7(1.6)	3(2.8)	4(1.3)	0.455
Surgery on thorax	15(3.5)	6(5.6)	9(2.8)	0.370
Surgery on brain	112(26.3)	38(35.5)	74(23.2)	0.135
Surgery on spine	21(4.9)	9(8.4)	12(3.8)	0.054
Thoracic close drainage	19(4.4)	6(5.6)	13(4.1)	0.740
Transcutaneous tracheostomy	101(23.7)	36(33.6)	65(20.4)	0.074

Abbreviations: IQR, interquartile range; BMI, body mass index; GCS, glasgow coma scale; ISS, injury severity score; CRP, C-reactive protein; DMV, duration of mechanical ventilation; RBC, red blood cell.

feature in the classification task, followed by age, BMI, CRP and ISS scores 48 hours after admission (Figure 4). In addition, the AUC of the RBNN reached 0.871 (Figure 5). The feature importance analysis of the RBNN model showed that VPC was the most vital feature in the classification task, followed by age and BMI. The accuracy and AUC of the other machine learning algorithms are shown in Table 3. The random forest classification achieved the highest accuracy, while the SGD classifier achieved the highest AUC.

Finally, we developed a decision tree using the CHAID growth approach to simplify interpretation in the clinic (Figure 6). We found that the algorithm correctly detected 86.4% of the cases. As an example of how to use the CHAID decision tree, if the patient was >46 years old, the number of NDMV cases was 49 (31%*37.1%), and the number of PDMV cases was 83 (31%*62.9%). Furthermore, when VPC was ≤17.6%, there were 21 PDMV cases (12%*41.2%), and the rest were normal cases (12%*58.8%). Finally, the number of PDMV cases caused by pneumothorax was 6 (6.1%

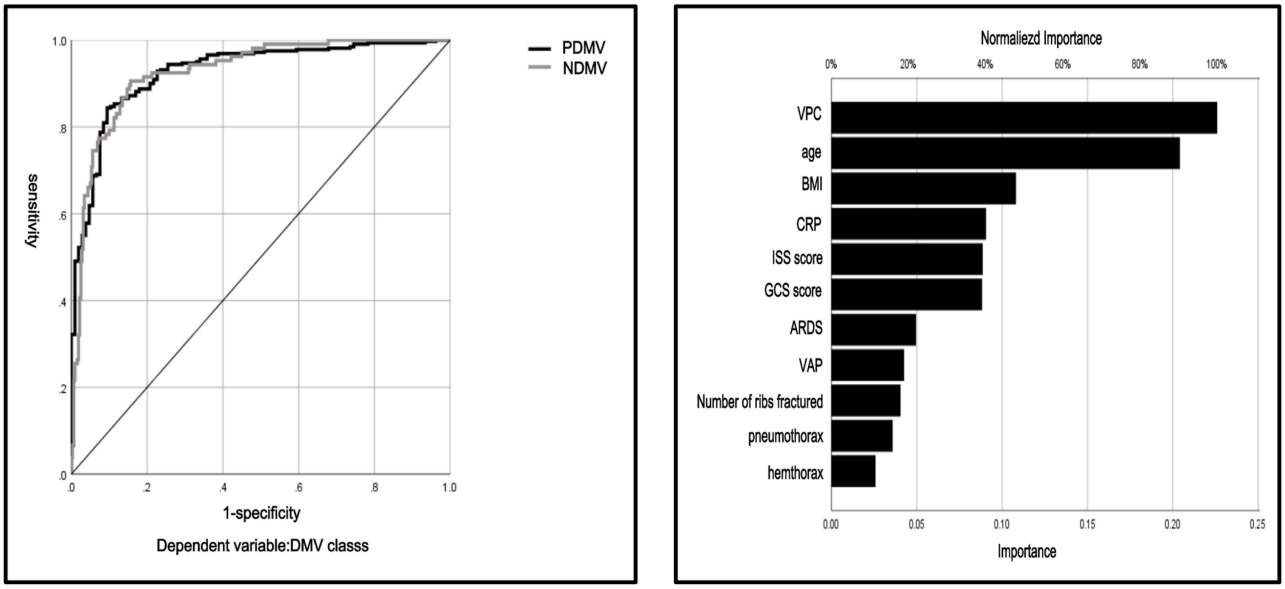

Figure 4 Prediction of DMV with multilayer perceptron (MLP). Input layer: feature variables (36units). Hidden Layer: 2units, activation function: hyperbolic tangent. Output layer: dependent variable DMV (2units), activation function: softmax, error function cross-entropy. The number of units in the hidden layer was determined by the testing data criterion: the best number of hidden units is the one that yields the smallest error in the testing data set. Train/Test/Validation split: 70/20/10. Percent in correct predictions on training set: 10.5%; percent in correct predictions on testing set: 15.4%; percent incorrect predictions on hold out set: 10.0%; NDMV refers to the prediction of the normal class; PDMV refers to the prediction of the prolonged DMV. AUC: 0.923(left pane). Feature importance analysis for predicting the DMV classes in the multilayer perceptron model (right pane).

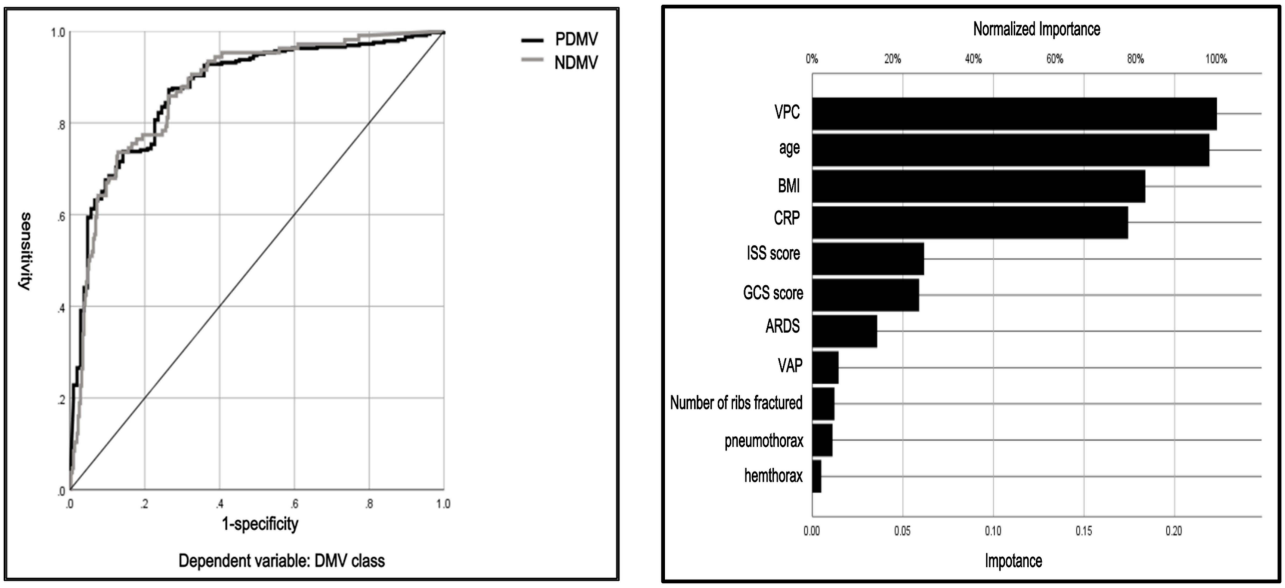

Figure 5 Prediction of DMV with radial basis function neural network (RBNN). Input layer: feature variables (36units). Hidden Layer: 5units, activation function: softmax. Output layer: dependent variable DMV (2units), activation function: identity, error function sum of of squares. The number of units in the hidden layer was determined by the testing data criterion: the best number of hidden units is the one that yields the smallest error in the testing data set. Train/Test/Validation split: 70/20/10. Percentage in correct predictions on training set: 12.5%; percent in correct predictions on testing set: 14.2%; percent incorrect predictions on hold out set: 13.6%; NDMV refers to the prediction of the normal class; PDMV refers to the prediction of the prolonged DMV. AUC: 0.871(left pane). Feature importance analysis for predicting the DMV classes in the RBNN (right pane).

*23.1%). Therefore, the probability of PDMV in a 48-year-old patient with a blunt-force chest injury with a VPC greater than 17.6% and a pneumothorax was 1.41%.

Discussion

BCT patients admitted to the ICU often require mechanical ventilation due to severe hypoxemia. The prognosis of PDMV patients is usually poor, with high in-hospital complications and mortality.[14] Over the past decade, researchers have found that a variety of factors can cause PDMV, including internal thoracic factors (VAP, PC, multiple rib fractures, hemothorax, pneumothorax, and ISS scores) and external thoracic factors (age, BMI, TBI, and GCS scores).[17–21] Despite all these findings, the probability of PDMV in BCT patients is still high, and there is a need for a reliable tool that can accurately predict PDMV in BCT patients.[8,9] We investigated whether a machine learning-based technique could be used

Table 3 Performance Measures for the Machine Learning and Deep Learnin Galgorithms to Predict the DMV (binary classification task).Analysis Was Done with k-Fold cross-Validation (k=3)

Algorithm	Accuracy	AUC
Logistic Regression	0.813	0.813
Random Forest classifier	0.875	0.812
SGD classifier	0.851	0.874
K-nearest neighbors	0.754	0.753
Decision Trees classifier	0.732	0.765
Gaussian Naive Bayes	0.781	0.764
Support Vector Machine	0.797	0.810

Abbreviations: AUC, area under the curve; Accuracy, TP +TN)/(TP+TN+FP+FN); SGD, stochastic gradient descent.

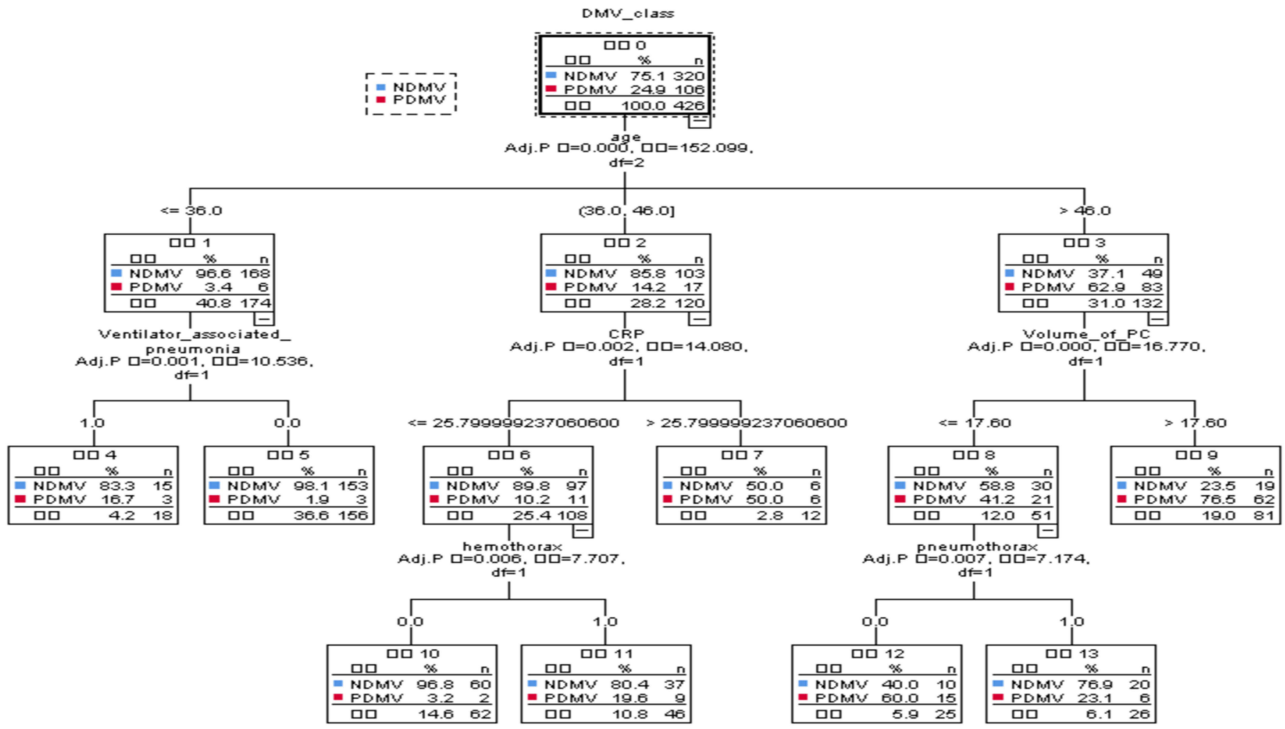

Figure 6 Decision tree with CHAID growing method. Five-fold cross-validation. Percent correct predictions with this algorithm: 86.4%.

to predict PDMV. Our findings suggest that DMV can be predicted using clinical data from BCT patients. Despite the small sample size in our study, the machine-learning algorithms showed promising results.

The results of a meta-analysis study showed that the development of machine learning for predicting DMV is hampered by sample size limitations, imperfect study designs, and the heterogeneity of techniques. Nevertheless, the combined algorithm of multiple prediction models can predict the duration of mechanical ventilation more accurately.[26] In addition, Parreco et al[27] reported the predictive value of the gradient increasing decision tree algorithm for DMV in critically ill patients, with an AUC=0.852. In this study, the gradient increasing decision tree algorithm had a high value in predicting PDMV, but there was a lack of analysis for the trauma population. Abujaber et al[28] compared the predictive value of different prediction models for PDMV in TBI patients and found that SVM had the highest predictive value with AUC=0.84. Lin et al[29] also compared the prediction of multiple prediction models on the PDMV of critically ill patients admitted to the ICU in a single center, and the results showed that the extreme gradient increasing (XGBoost) model had the highest predictive value (AUC=0.908), with the feature importance including ventilator parameter settings, fluid/nutrition and physiological indicators in turn. Our study cohort had two significant clusters, high-risk and low-risk, which indicated the validity of our hypothesis that PDMV was associated with other characteristics. This study showed that machine learning techniques could effectively predict NDMV and PDMV, with AUC values of 0.753–0.923. As our study is the first to use machine learning algorithms to predict DMV in BCT patients, it is not possible to compare the results with those of other studies. However, our study provides insight into the specific risk profile of BCT patients and better adjustment of resource allocation and weaning plans. It is also possible to create an open-source web-based DMV prediction tool based on the variables used by the machine learning algorithm.

Most of the previous studies were single-center or retrospective cohort studies, and few researchers used machine learning algorithms to predict PDMV in BCT patients. Mahmood et al[21] found that a VPC greater than 20% and ARDS were important predictors of DMV prolongation. Previous studies by our research group also found that a VPC greater than 23.5% could predict tracheotomy in patients with multiple rib fractures.[30] This was mainly because PC calculated based on 3D reconstruction technology reflects the severity of pulmonary contusion, and moderate to severe PC is prone to hypoxia and secondary pulmonary infection and ARDS, which are the main factors causing PDMV.[21] Overall, VPC is

relevant for multiple parameters (ARDS, VAP), and it may be important for DMV as well. In addition, our study found that age, BMI, ISS score and GCS score were predictors of DMV, which was consistent with the results of other studies.[15–21] Our study quantified DMV risk by including all potential features in the evaluation, performing a significance analysis of features, and visualizing the results. The findings of our study may help clinicians evaluate BCT patients before intubation, more accurately set the expectations of patients and relatives, and help the whole monitoring team develop a personalized treatment and care plan to shorten the duration of DMV and increase patient weaning safety and satisfaction.

We also found that CRP levels 48 hours after admission may be associated with PDMV in BCT patients. CRP is a cytokine involved in the acute phase of inflammation that is mainly released by interleukin-6 and other proinflammatory cytokines.[31] When CRP binds to the Fc-γ receptor, CRP activates the classical complement cascade and accelerates phagocytosis.[32] In addition, increases in CRP may be more pronounced in disease processes observed earlier than in other nonspecific markers, such as fever, and CRP levels may decline rapidly during recovery. Therefore, CRP can be used to screen for inflammation in the early stage of the disease and as an assessment tool for the effectiveness of treatment. A prospective observational study involving 72 critically ill trauma patients found that a CRP level greater than 10 mg/dl measured 48 hours to 72 hours after admission was the most effective predictor of mechanical ventilation longer than 7 days, followed by BMI.[33] However, another study of mechanically ventilated patients with long-term chronic respiratory failure found that CRP did not predict successful weaning at a rate of 9% at 60 days. This suggests that CRP has low predictive value for the duration of mechanical ventilation in patients with chronic diseases.[34] Other researchers have also found that elevated CRP levels within 48 hours of cardiac or noncardiac surgery can increase the risk of cardiovascular adverse events in hospitalized patients, and the risk of morbidity and mortality also significantly increases.[35] The reason may be related to the degree of surgical injury.[36] Overall, evidence on the effect of CRP on DMV in BCT patients at 48 hours after admission is limited and needs to be validated in more prospective studies. The inclusion of CRP as a biological marker in our algorithm led to an increase in diagnostic accuracy. Therefore, it is necessary to include other biomarkers to evaluate the diagnostic performance of the models in the future.

Our study found no significant difference in the proportion of individuals with chronic heart failure between the high-risk and low-risk groups. Interestingly, Cardiopulmonary interactions are present throughout the patient's ventilator weaning, and the transition from positive pressure to spontaneous breathing causes abrupt changes in cardiac load and an increase in oxygen demand. These alterations may place an undue burden on the respiratory and cardiovascular systems, causing a rapid and significant increase in left ventricular filling pressure and ultimately leading to wean-induced pulmonary edema.[37] We hypothesize that this lack of difference may be attributed to the absence of a significant increase in the proportion of patients with chronic heart failure who experience severe acute pulmonary edema during the weaning process. Nevertheless, further prospective studies are required to validate our conclusions.

Despite the novelty and strengths of our machine learning algorithm, some potential limitations also existed. First, this was a retrospective and single center study, so prospective investigation was still lacking, so external validation is needed in the future. Second, although we included many important variables from an extensive literature review, it was still possible that we might have missed some other potentially relevant variables, such as biomarkers similar to CRP. These aspects should be addressed in our future research.

Conclusion

Mechanical ventilation is one of the most common treatments for patients with BCT; however, PDMV can cause a series of serious complications. Patient-centered outcome prediction models to predict DMV can effectively use the existing social medical resources, allowing clinicians and medical decision makers to choose treatment options from different disciplines and formulate relative priority intervention programs. Our findings suggest that machine learning techniques can effectively predict risk factors for PDMV in BCT patients. Further prospective studies are needed for external validation and the development of a tool that can provide reliable predictive performance in the clinic.

Ethics Approval

The studies involving human participants were reviewed and approved by Affiliated Hospital of Yangzhou University (2021-YKL3-01-001).

Consent to Participate

Due to the observational nature of the study, written informed consent was waived for all enrolled patients.

Consent to Publish

The authors affirm that human research participants provided informed consent for publication.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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