Original Article

Artificial intelligence assisted nutritional risk evaluation model for critically ill patients: Integration of explainable machine learning in intensive care nutrition

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Background and Objectives: Critically ill patients require individualized nutrition support, with assessment tools like Nutrition Risk Screening 2002 and Nutrition Risk in the Critically Ill scores. Challenges in continuous nutrition care prompt the need for innovative solutions. This study develops an artificial intelligence assisted nutrition risk evaluation model using explainable machine learning to support intensive care unit dietitians. **Methods and Study Design:** Ethical approval was obtained for a retrospective analysis of 2,122 patients. Nutrition risk assessment involved six dietitians, with 1,994 patients assessed comprehensively. Artificial intelligence models and shapley additive explanations analysis were used to predict and understand nutrition risk. **Results:** High nutrition risk (35.2%) correlated with elder age, lower body weight, BMI, albumin, and higher disease severity. The AUROC scores achieved by XGBoost (0.921), CatBoost (0.926), and LightGBM (0.923) were superior to those of Logistic Regression. Key features influencing nutrition risk included Acute Physiology and Chronic Health Evaluation II score, albumin, age, BMI, and haemoglobin. **Conclusions:** The study introduces an artificial intelligence assisted nutrition risk evaluation model, offering a promising avenue for continuous and timely nutrition support in critically ill patients. External validation and exploration of feature relationships are needed.

Key Words: artificial intelligence, machine learning, nutritional risk, ICU, critical illness

INTRODUCTION

Critically ill patients are highly heterogeneous, and there is no one-size-fits-all approach to nutrition support that can be applied universally. However, most researchers agree that patients with a high nutrition risk require aggressive nutrition support to improve their outcomes. American Society for Parenteral and Enteral Nutrition guideline suggested using Nutrition Risk Screening 2002 (NRS2002), Nutrition Risk in the Critically Ill (NUTRIC) score to screen high nutrition risk patients.[1] In the European Society for Parenteral and Enteral Nutrition guidelines, there is no gold standard for defining nutrition risk. However, patients who have been admitted to the intensive care unit for longer than 48 hours are assumed to be at risk for malnutrition.[2,3]

The NUTRIC score includes age, Acute Physiology and Chronic Health Evaluation II (APACHE II) score, Sequential Organ Failure Assessment (SOFA) score, comorbidities, Interleukin-6 (IL-6) levels, and days from hospital admission to intensive care unit (ICU) admission.[4] However, for practical purposes, IL-6 is often neglected.[5] Notably, the NUTRIC score includes disease severity scores instead of significant nutrition markers. The NRS2002 takes into account BMI, body weight loss, appetite, and disease severity, but it is not well validated in critically ill patients.[6]

Registered dietitians in the ICU play a crucial role in the comprehensive evaluation of nutrition risk in critically ill patients. However, in the real world, continuity of nutrition care in the ICU can be a problem during nighttime and holidays due to a shortage of staff.[7,8] Registered dietitians are facing increasingly more challenges, especially during the Coronavirus disease 2019 (COVID-19) pandemic.[9]

Recently, artificial intelligence and machine learning have been widely used in medical care to assist with clinical decision-making and improve care efficiency.[10] For example, Sharma et al. demonstrated the use of

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machine learning methods to identify patients at risk of malnutrition, while Wang et al. reported on an artificial intelligence-assisted tool for evaluating nutritional status in elderly patients.[11,12] Yin et al. also developed a machine learning-assisted decision-making system to recognize malnutrition in cancer patients.[13] However, these studies have mainly focused on elderly or cancer patients rather than critically ill patients and did not utilize interpretable machine learning to aid in decision-making. If artificial intelligence can simulate the work of registered dietitians, it could provide continuous nutrition support for critically ill patients.

The present study aims to develop an artificial intelligence-assisted nutrition risk evaluation model using explainable machine learning methods to support the work of registered dietitians in the ICU.

METHODS

Ethical approval

This study was approved by the Institutional Review Board of the Taichung Veterans General Hospital (TCVGH: CE21134A). All data were obtained from electronic medical records and de-linked before analyses. Informed consent was waived because of the de-linked data was retrieved retrospectively.

Study population

This study was conducted at TCVGH, a tertiary-care referral hospital in central Taiwan, from January 2016 to December 2019. Inclusion criteria comprised respiratory failure requiring ventilator support and ICU admission. Exclusion criteria included ICU stays less than 3 days, age less than 20 years, Human Immunodeficiency Virus (HIV) or pregnant patients (Figure 1). A total of 1,994 patients meeting the criteria were screened from 2,122 potential candidates.

Nutrition risk assessment consensus

The definition of high nutritional risk in our study is based on the clinical experience of dietitians, incorporating both established guidelines and practical considerations in ICU settings. To establish a consensus definition, we engaged six senior dietitians with over 10 years of ICU experience. The process included the integration of multiple guidelines and tools, such as the NRS 2002 score, the NUTRIC score, the 2019 ESPEN guideline, and an evaluation of potential refeeding syndrome. Nutritional risk was assessed across four dimensions: nutritional status, disease severity, age, and the presence of pressure ulcers. Each dimension was scored on a scale of 1 to 3 according to severity, and through three rounds of consensus meetings, a threshold score of ≥5 was determined to classify patients as at high nutritional risk. This approach sought to balance clinical rigor with feasibility in clinical workflow. The inter-rater reliability, assessed using Fleiss' kappa, was 0.64, indicating substantial agreement.

Variables categorized by main clinical domains

The dataset was collected by dietitians from electronic medical records, capturing data 24 hours before ICU admission and 48 hours after ICU admission. It includes demographic information such as age and sex, anthropometric data like height and body weight, biochemical markers such as serum albumin level, basic laboratory results, disease severity scores including APACHE II and SOFA scores, and information on comorbidities. Outcome measures encompassed hospital mortality, length of ventilator dependency, ICU stay, and total hospital stay.

Building the prediction model

We randomly selected 80% patients for model training and validation using 5-fold cross-validation, and the other 20% for model evaluation (Figure 2). Four algorithms including Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBOOST), Light Gradient Boosting Machine (LightGBM), and Logistic regression were selected for model determination. Predictive features included demographic data, clinical indicators, and other variables typically used by dietitians. The outcome was the nutritional risk classification assigned by the dietitians. Additionally, we employed a wrapper feature selection approach and identified that the top five features yielded the highest accuracy.

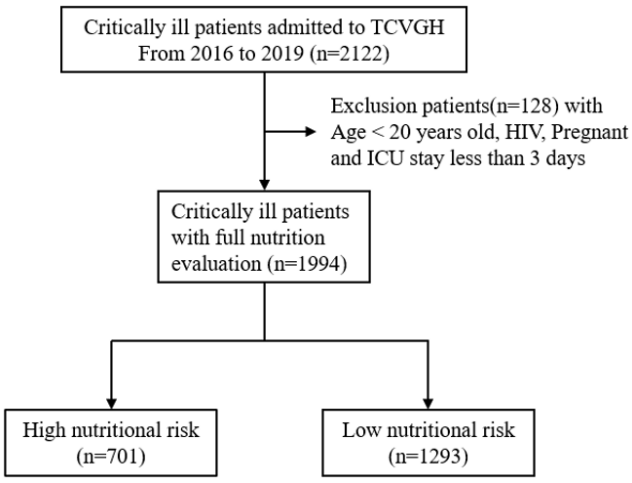


Figure 1. Flowchart of subject enrolment. TCVGH: Taichung Veterans General Hospital; HIV: Human Immunodeficiency Virus; ICU: Intensive Care Unit.

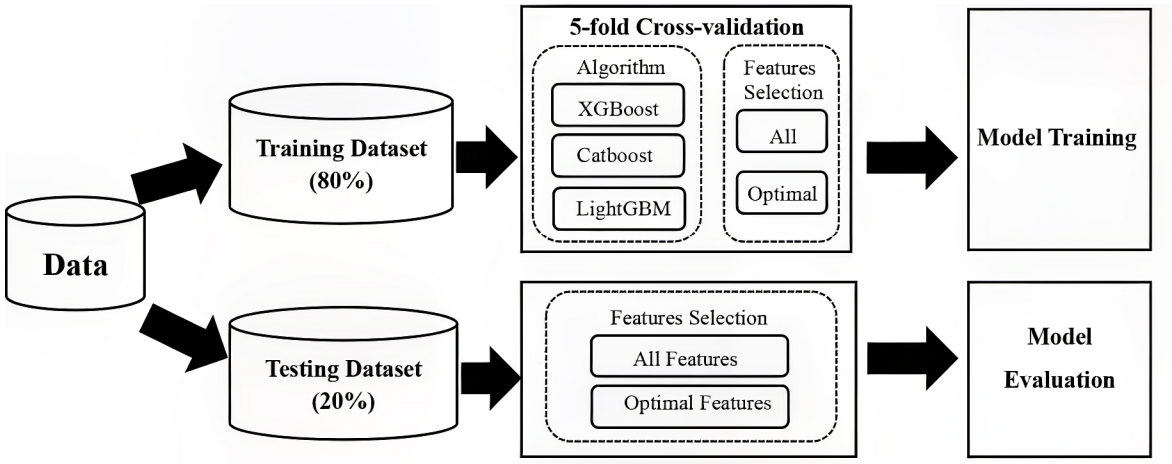


Figure 2. The flow diagram of the study

Shapley Additive Explanations (SHAP)

SHAP is a game-theoretic approach for explaining the output of a machine learning model.[14] It combines optimal credit allocation with local explanations by utilizing classic Shapley values from game theory and their relevant extensions. Shapley values, widely employed in cooperative game theory, possess desirable properties. SHAP values offer a comprehensive method to explain the results of our ML model and provide consistent and locally accurate attribution values for each feature. In our study, SHAP is used to explore the relationship between the nutritional risk outcome and features.

Statistical analysis

Data analysis was conducted using SPSS software (version 22.0; International Business Machines Corp., Armonk, NY, USA). A p-value of ≤ 0.05 was established as statistically significant. Continuous data were expressed as mean ± standard deviation. Categorical variables were described as counts and percentages. A comparison of interval data between the high and low nutritional risk groups was performed using the t-test or chi-square test. Python version 3.6.9 was utilized to evaluate the discrimination, accuracy, and applicability of the models in the testing sets using receiver operating characteristic curve analysis and decision curve.

RESULTS

Demographic data

A total of 1,994 patients were enrolled and 65 features were selected in this study. The mean age was 65.6 ± 16.3years, and 35.4% (706/1994) of patients was female. 701 patients were belonging to high nutritional risk group (35.2%).

Patients with high nutritional risk were associated with elder age (72.8 ± 14.6 vs. 61.7 ± 15.9, $p < 0.01$), lower body weight (58.6 ± 12.6 vs. 64.4 ± 14.2, $p < 0.01$), lower BMI (22.7 ± 4.52 vs. 24.3 ± 4.79, $p < 0.01$) and lower albumin (2.58 ± 0.57 vs. 3.14 ± 0.64, $p < 0.01$) compared to patients with low nutritional risk group (Table 1).

Disease severity such as APACHE II and SOFA score were higher in high nutritional risk group compared to low nutritional group patients. The clinical outcomes including ICU days, ventilator use days, hospital days, and mortality were significantly worse in high nutritional risk group patients (Table 1).

Explanation of the model

The performance of the model

Four classification algorithms were trained using 5-fold cross-validation. The results are summarized in Table 2. By comparing the results of all features in training dataset, we found that XGBoost and Catboost performed similarly and were the top performers across most metrics, particularly in terms of Precision, Sensitivity, and area under receiver operating characteristic curve (AUROC) in the 5-fold cross-validation. LightGBM followed closely, while Logistic Regression showed notably lower performance, especially in Specificity and AUROC. In the testing dataset, the performance metrics of the algorithms slightly decreased but still remained relatively high. The decision curve of the four algorithms in test dataset are shown in Figure 3. We found that Catboost, XGBoost, and LightGBM models exhibited higher net benefit than logistic regression as well as default strategies of treating all patients or no patients.

SHAP summary plot

To enable the visualized interpretation of key features of the model, we used a SHAP plot to illustrate how these features affect nutrition risk. Figure 4a illustrated the SHAP plot ranks features based on their overall impact on the prediction. The features are listed top-down with decreasing importance. Only the top 20 features are listed, and categorical variables are split into one bar per category. We found that APACHE II, Albumin, age, BMI, and Haemoglobin are the characteristics that have the greatest influence on nutritional risk.

Figure 4b illustrates a small observed value of the characteristic factor. Features with higher total SHAP values (red) had a stronger influence on increasing the prediction, while those with lower values (blue) had a greater effect on decreasing it. The x-axis displays the individual SHAP values for each patient. The results show that APACHE II score and age are positively correlated with the nutritional risk. Albumin, BMI, and Hemoglobin are negatively correlated with the nutritional risk.

Table 1. Patients' demographic characteristics, severity score, clinical outcomes

Variables	All (n = 1994)	High nutritional risk group (n = 701)	Low nutritional risk group (n = 1293)	*p*-value
Demographic data				
Age (years)	65.6±16.3	72.8±14.6	61.7±15.9	<0.001**
Sex (female)	706 (35.4%)	262 (37.4%)	444 (34.3%)	0.192
Weight (kg)	62.4±14.0	58.6±12.9	64.4±14.2	<0.001**
Body mass index	23.7±4.75	22.7±4.52	24.3±4.79	<0.001**
Albumin (mg/dL)	2.92±0.67	2.58±0.57	3.14±0.64	<0.001**
Comorbidities (n, %)				
Diabetes mellitus	658 (33.0%)	256 (36.5%)	402 (31.1%)	0.016*
Liver cirrhosis	157 (7.87%)	70 (9.99%)	87 (6.73%)	0.013*
Uremia	633 (31.6%)	287 (40.9%)	346 (26.8%)	<0.001**
Central nerve system disorder	407 (20.4%)	142 (20.3%)	265 (20.5%)	0.946
Chronic lung disease	300 (15.1%)	126 (18.0%)	174 (13.5%)	0.009**
Immunocompromised disorders	175 (8.78%)	76 (10.8%)	99 (7.66%)	0.021*
Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin	661 (33.2%)	273 (38.9%)	388 (30.0%)	<0.001**
Congestive heart failure	358 (18.0%)	143 (20.4%)	215 (16.6%)	0.042*
Chronic lung disease	300 (15.1%)	126 (18.0%)	174 (13.5%)	0.009**
Disease severity scores				
APACHE II score	23.8±7.80	29.4±5.62	20.4±6.96	<0.001**
SOFA score	7.55±3.91	9.54±3.69	6.46±3.59	<0.001**
Clinical outcome				
Length of ICU stay (day)	10.3±10.1	13.4±10.6	8.70±9.48	<0.001**
Length of ventilator dependency (day)	5.27±11.0	7.49±12.4	4.06±9.89	<0.001**
Length of hospital stay (day)	27.0±27.3	31.4±25.7	24.6±27.9	<0.001**
Hospital mortality	478 (24.0%)	252 (36.0%)	226 (17.5%)	<0.001**
ICU (n, %)				<0.001**
Medical	1432 (71.8%)	562 (80.2%)	870 (67.3%)	
Surgical	562 (28.2%)	139 (19.8%)	423 (32.7%)	

Values are mean ± SD. APACHE II: Acute Physiology and Chronic Health Evaluation II; SOFA: Sequential Organ Failure Assessment. ICU: intensive care unit
* $p < 0.05$, ** $p < 0.01$.

Table 2. Model performance using full features

Classifier	Precision	Sensitivity	Specificity	Accuracy	AUROC
5-fold CV					
XGBoost	0.832 ± 0.039	0.915 ± 0.020	0.780 ± 0.044	0.868 ± 0.027	0.928 ± 0.023
CatBoost	0.832 ± 0.039	0.916 ± 0.018	0.771 ± 0.059	0.865 ± 0.031	0.932 ± 0.024
LightGBM	0.803 ± 0.039	0.897 ± 0.022	0.780 ± 0.046	0.856 ± 0.027	0.925 ± 0.025
Logistic Regression	0.737 ± 0.069	0.872 ± 0.040	0.655 ± 0.069	0.796 ± 0.040	0.863 ± 0.035
Testing					
XGBoost	0.779	0.876	0.801	0.850	0.921
CatBoost	0.803	0.888	0.837	0.869	0.926
LightGBM	0.784	0.876	0.823	0.857	0.923
Logistic Regression	0.713	0.849	0.688	0.792	0.852

XGBoost, eXtreme Gradient Boosting; CatBoost, Categorical Boosting; LightGBM, Light Gradient Boosting Machine; AUROC, area under the receiver operating characteristic curve; CV, cross-validation.

SHAP dependence plot

We further used SHAP dependence plot to illustrate how the top 5 features influenced the outcome of nutritional risk (Figure 5). In SHAP dependence plot, each point represents an individual patient, thereby illustrating how the attribution importance of baseline variables varies with their values. The SHAP values exceeding zero represented an increased risk of nutrition.

We found that age is about less than 70 (Figure 5a), APACHE II is about less than 25 (Figure 5b), which is predicted to be a low nutritional risk; on the contrary, BMI is about less than 20 (Figure 5c), Alb is about less than 3 (Figure 5d), and and Hgb approximately below 11 (Figure 5e) predict high nutritional risk.

SHAP individual force plots

We selected two patients for analysis using SHAP individual force plots. In Figure 6a, the AI predicted a high nutritional risk, contrary to the dietitian's assessment of low risk. The AI model considered five features (Age, APACHE II, BMI, Albumin, Haemoglobin), all leaning towards a high nutritional risk, cumulatively predicting a 96% probability of high risk. Despite the patient's severe

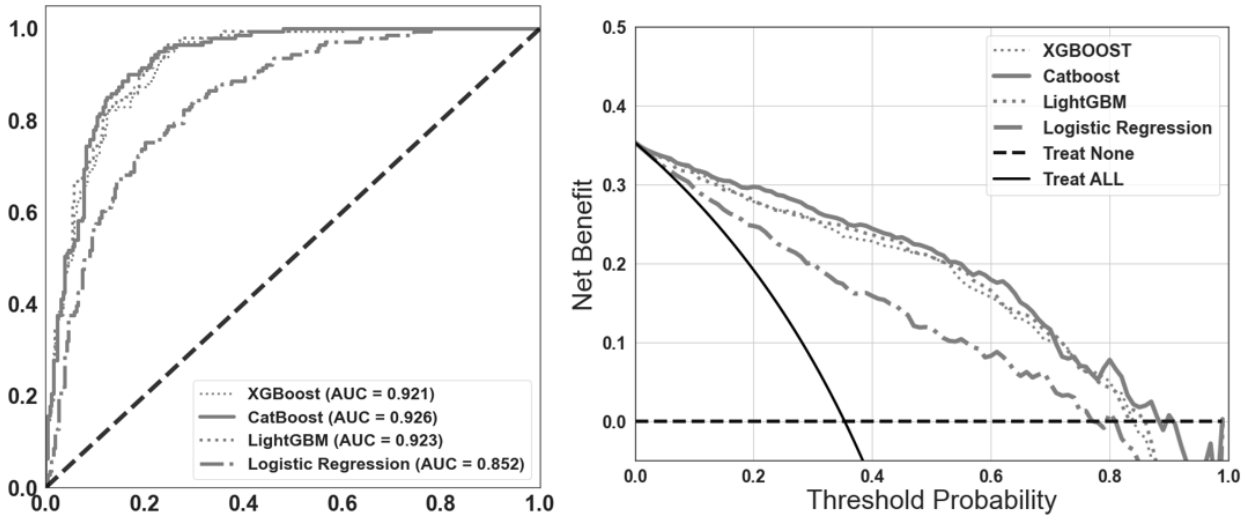


Figure 3. Receiver operating characteristics curves and decision curve analysis

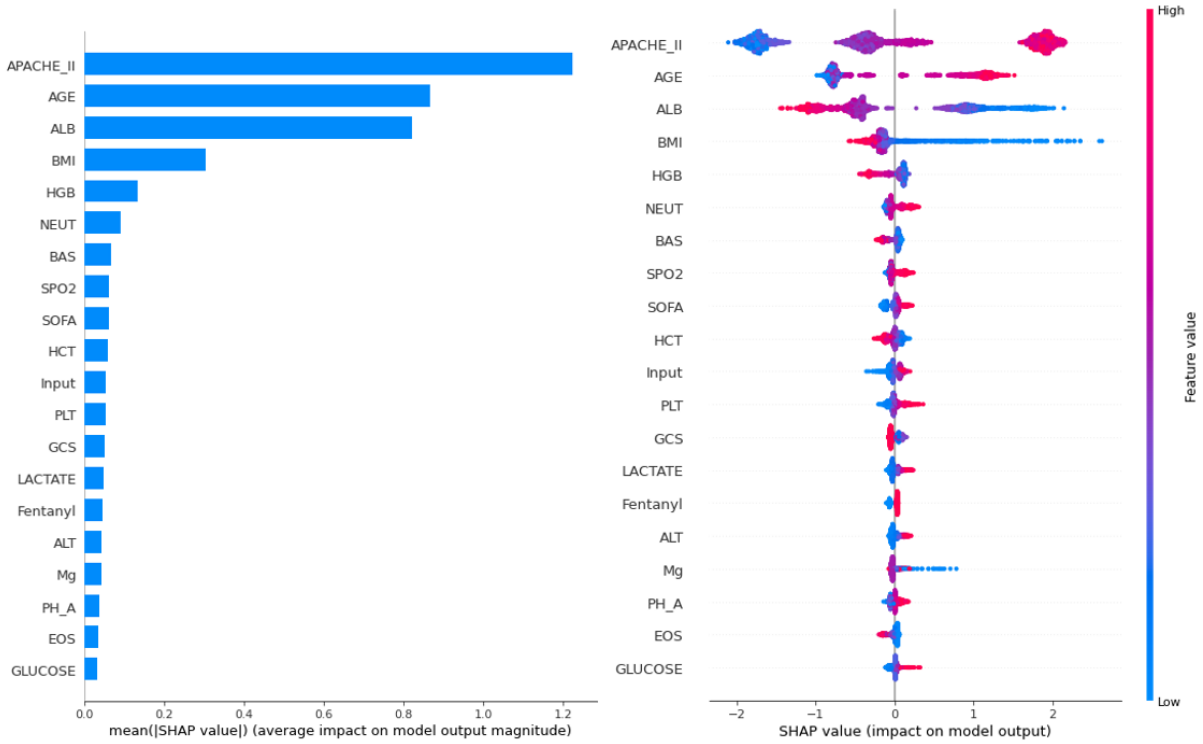


Figure 4. Global interpretation of Catboot. The APACHE II scores and age were positively correlated with nutritional risk, while albumin (Alb), BMI, and Haemoglobin (Hgb) levels were negatively correlated with nutritional risk

illness, their nutritional status was good, leading the dietitian to assess them as low risk. In Figure 6b, the AI predicted a low nutritional risk, while the dietitian deemed it high risk. Within the AI model, three features (age, BMI, Haemoglobin) inclined towards low risk, while APACHE II and albumin tended towards high risk, resulting in an overall prediction of only an 18% probability of high risk. Although the severity of the disease was low, the patient's nutritional condition was poor, prompting the dietitian to consider it high risk.

Comparative performance with the NUTRIC score

To evaluate the predictive performance of the dietitian-assessed nutrition risk model, we compared it to the NUTRIC score in predicting ICU stays exceeding 7 days using our dataset. Both models were assessed using receiver operating characteristic (ROC) curves, with the Area Under the Curve (AUC) as the performance metric.

While both models achieved AUC values above 0.5, indicating predictive capability, the dietitian-assessed model demonstrated slightly superior discrimination with higher AUC values, despite the modest differences. These findings suggest that the dietitian-assessed model may offer a more nuanced and clinically relevant tool for identifying high-risk patients in ICU settings, particularly for predicting prolonged ICU stays, compared to the NUTRIC score (Figure 7).

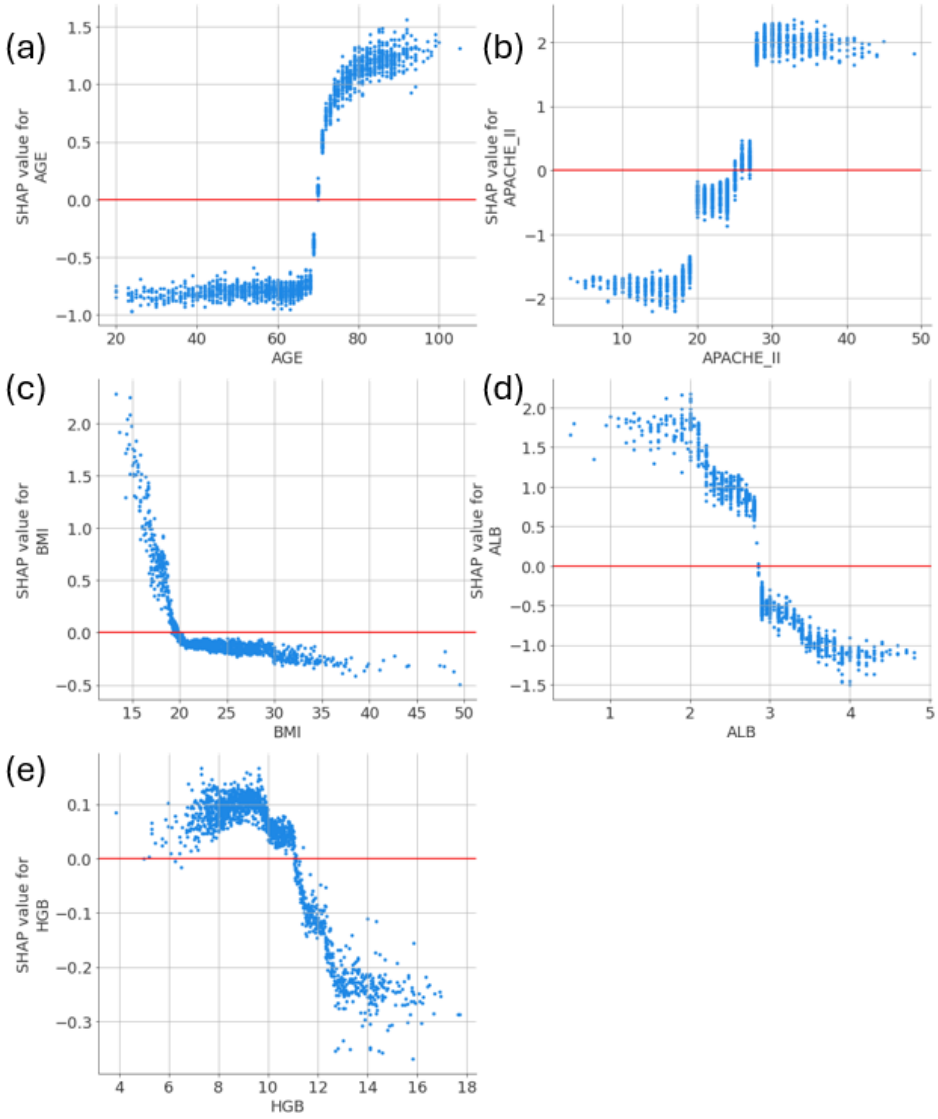


Figure 5. SHAP dependence plot of the CatBoost model in predicting nutrition risk. (a) Age, (b) APACHE II, (c) BMI, (d) albumin (ALB), (e) Haemoglobin (HGB).

DISCUSSION

In the study, we identified the predictive risk factors for nutrition in critically ill patients and developed a machine learning-based predictive model. Our findings revealed that models such as XGBoost, CatBoost, and LightGBM yielded superior predictive performance. These results underscore the efficacy of high-performance gradient boosting frameworks in accurately identifying nutritional risks.

We further utilized explainable AI methods to identify key features associated with nutritional risk, yielding results that align with prior research. For example, previous studies have indicated a link between nutritional risk, low BMI, and adverse health outcomes, including increased mortality.[15,16] Additionally, a positive correlation was observed between high nutritional risk and elevated APACHE II scores.[17] Furthermore, the introduction of nutritional support was found to significantly improve disease severity.[18] The findings suggest that the predictive model shows promise in identifying clinical nutrition-related risks. While the results are encouraging, further validation is required to fully confirm its effectiveness in clinical settings.

The prognosis for malnutrition in critically ill patients is undoubtedly poor. However, inflammation during the acute stage may be a reason why critically ill patients require nutrition support.[2,19] Theoretically, critically ill patients with high nutrition risk would recover well after receiving optimal nutrition support. The Heyland et al observational study demonstrated that higher caloric intake reduced mortality in high nutrition risk patients.[4]

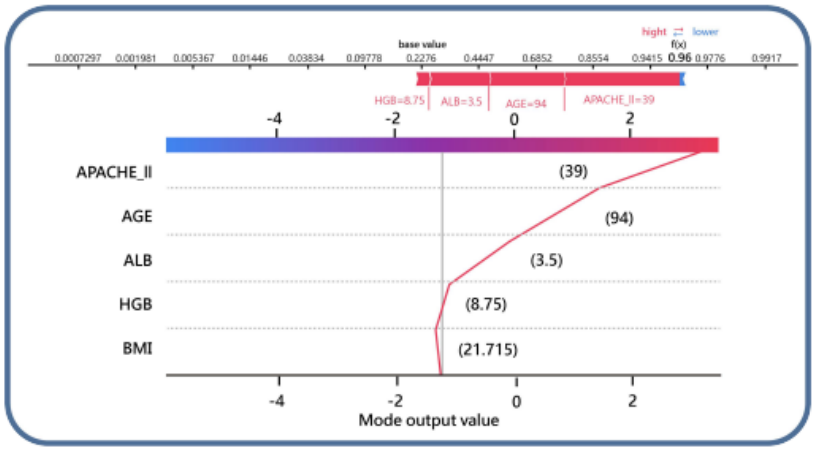
However, a subsequent randomized controlled trial prescribed full caloric feeding or trophic feeding in high nutrition risk patients, with hospital mortality rates of 24% and 19%, respectively.[20] The hospital mortality rate seemed higher in the full caloric feeding group, but this difference did not reach statistical significance. In a post-hoc analysis of the Permissive Underfeeding versus Target Enteral Feeding in Adult Critically Ill Patients (PermiT) study, there was no difference in 90-day mortality between high and low nutrition risk patients who received permissive underfeeding.[21] The NUTRIC score consists of only six items, which may make it difficult to

(a) Case-1

Dietitians level – low nutrition risk

Nutritional status	Severe disease	age	Pressure sore
0	3	1	0

AI prediction 0.96 – high risk



(b) Case-2

Dietitians level – high nutrition risk

Nutritional status	Severe disease	age	Pressure sore
3	1	1	0

AI prediction 0.18 – low nutrition risk

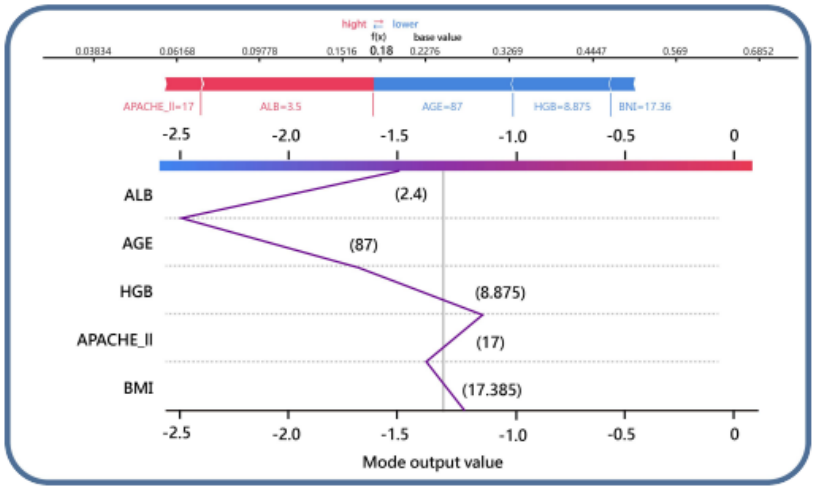


Figure 6. Force plots for a patient: (a) predicted to be at high risk, but assessed as low risk by the dietitian (prediction 0.96). (b) predicted to be at low risk, yet considered high risk by the dietitian (prediction 0.18)

accurately identify patients with high nutrition risk with limited information.

Implementation of feeding protocols is another form of nutrition support that can help overcome feeding barriers. Feeding protocols can improve the efficiency of caloric intake.[22] In a large randomized controlled trial, Ke et al. optimized nutrition support by implementing an evidence-based feeding guideline.[23] The eligible patients had at least one more organ system failure and expected ICU stay of more than 7 days. The intervention group received more enteral nutrition and less parenteral nutrition in the first 2 days, but the intervention did not result in a significant reduction in 28-day all-cause mortality. The study did not find any improvement in outcomes, despite using much evidence guided interventions, including NUTRIC score. Conversely, the NRS 2002 does include some nutrition parameters but lacks specific items for critically ill patients. Combining the NUTRIC and NRS 2002 scores did not yield better predictive values either.[24] Due to the complexity of critically ill patients, current nutrition risk evaluation tools might not suffice to replace the role of a registered dietitian in rating the nutrition risk of ICU patients.

Our study found differences in clinical outcomes based on the nutrition risk groups as labelled by registered dietitians. However, it's worth noting that nutrition risk evaluation alone may not fully predict clinical outcomes without considering the impact of nutrition support.[25-28] The purpose of nutrition risk evaluation should be to guide clinicians in providing appropriate nutrition support. Due to the retrospective design of our study, we were unable to provide detailed information on caloric intake for each nutrition risk group.

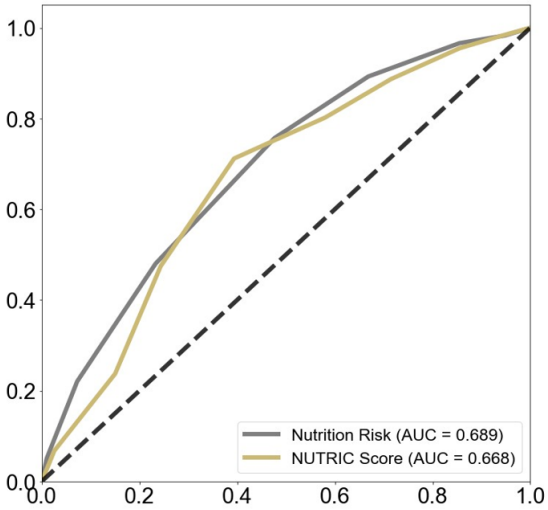
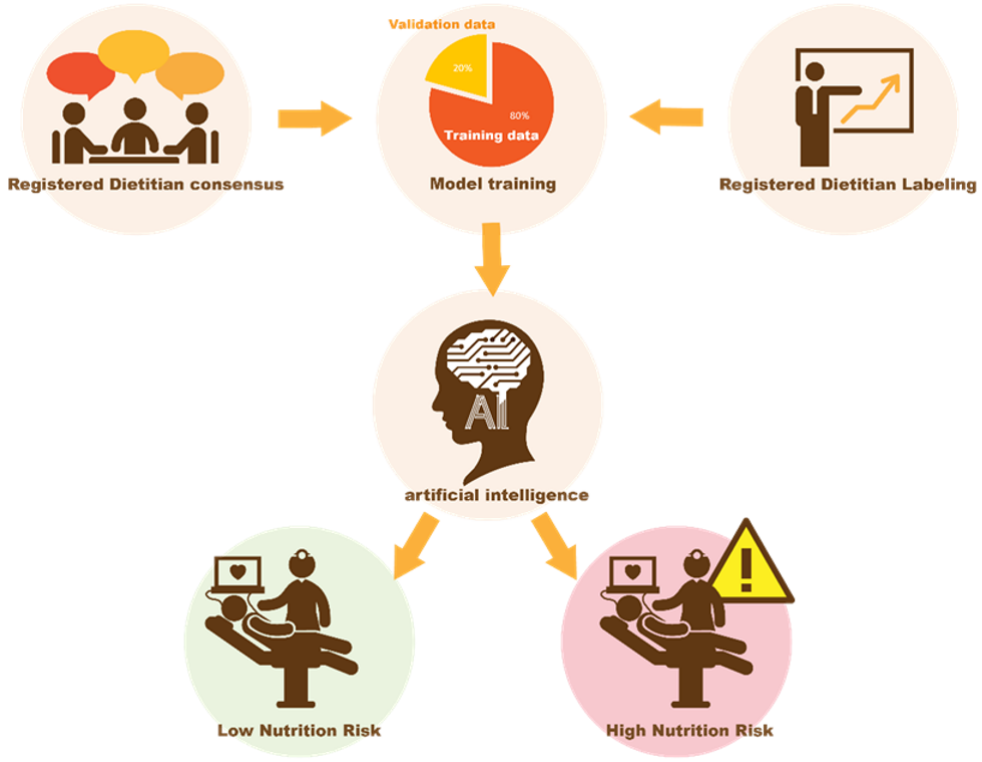


Figure 7. Comparative performance of dietitian-assessed nutrition risk and the NUTRIC score



Graphical abstract.

However, it is not feasible for a registered dietitian to be available 24/7 in the ICU, while an AI system could be. We can develop a nutrition risk prediction model by training AI to emulate the practices of registered dietitians in the ICU. In recent years, artificial intelligence and machine learning methods have been widely used in critically ill patients.[10] However, few artificial intelligence models have been introduced to predict nutrition status in critically ill patients, with most models focusing on cancer patients.[13] Given the complexity of critically ill patients and shortage of healthcare personnel, an artificial intelligence model to help intensivists assess nutrition risk in critically ill patients is imperative.[29] Our study has addressed this gap by developing a nutrition risk prediction model

In our final model, we found that APACHE II, age, BMI, albumin, and haemoglobin were the five major features that influence nutrition risk. However, haemoglobin is a rare item in terms of assessing nutrition risk for registered dietitians. Anaemia is common in critically ill patients, with approximately two-thirds of patients having haemoglobin levels less than 12 g/dL upon admission to the ICU.[30,31] There are several reasons for anaemia in ICU patients, including bleeding, chronic disease, and malnutrition, among others. Wu et al reported that critically ill patients with haemoglobin levels less than 10 g/dL were associated with higher one-year mortality in the surgical ICU.[32] Rasmussen et al demonstrated that haemoglobin levels less than 10 g/dL were associated with greater than 2.6 times higher 90-day mortality in patients with chronic

obstructive pulmonary disease and respiratory failure.[33] Taken together, anaemia may be one of the risk factors for poor outcomes in critically ill patients, which is consistent with our present findings. However, a well-conducted study is still needed to establish the relationship between anaemia and nutrition risk.

Our research revealed instances where prediction results differed from dietitians' assessments. Two key reasons contribute to this discrepancy. Albumin Initially considered a robust nutritional indicator, Albumin was later found to be influenced by inflammation in the blood, leading to value decreases due to redistribution. Consequently, many nutrition screening tools exclude albumin. However, the 2021 American Society for Parenteral and Enteral Nutrition guidelines reintroduced Alb as a relevant marker for inflammation and malnutrition.[34] Nonetheless, its accuracy can be compromised if patients receive albumin injections when transitioning from a ward to an ICU.

Dietitians often rely on the patient's food intake status and weight changes before ICU admission to assess nutritional risks. However, this information is frequently described in text rather than systematically recorded, making it challenging to incorporate into machine learning features.

While our study demonstrated that artificial intelligence significantly aids registered dietitians with impressive accuracy, it is important to acknowledge certain limitations. First, our study was conducted at a single centre, and although our model exhibits high accuracy, external validation is essential to fortify the robustness of our present model. Second, certain informative features are recorded in language by nursing staff, and we have not yet analysed this information without employing a natural language processing model. Third, the currently available data did not include information on body weight loss status prior to admission. Nevertheless, our dataset, collected from 1,994 patients who underwent comprehensive nutritional risk assessment, was labelled by six experienced dietitians after achieving consensus and has demonstrated good inter-rater reliability.

Conclusions

Machine learning is emerging as a novel contributor to clinical nutrition. Employing machine learning to predict patients' nutritional risk not only addresses the shortage of dietitians and the absence of clinical nutrition care during holidays but also provides healthcare professionals with insights into patients' nutritional status. This allows for increased attention and more timely, accurate nutritional support for patients at high nutritional risk.

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CONFLICT OF INTEREST AND FUNDING DISCLOSURE

The authors declare no conflict of interest.

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