ARTICLE IN PRESS

BURNS XXX (XXXX) XXX–XXX

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/burns

Machine learning approach for predicting inhalation injury in patients with burns

Shih-Yi Yang [a], Chih-Jung Huang [a], Cheng-I. Yen [a], Yu-Ching Kao [b], Yen-Chang Hsiao [a], Jui-Yung Yang [a], Shu-Yin Chang [a], Shiow-Shuh Chuang [a], Hung-Chang Chen [a,*]

[a] Department of Plastic and Reconstructive Surgery, Chang Gung Memorial Hospital, Linkou, College of Medicine, Chang Gung University, Taoyuan, Taiwan, ROC

[b] Muen Biomedical and Optoelectronic Technologies Inc, China

ARTICLE INFO

Article history:
Accepted 16 March 2023

Keywords:
Coronavirus disease (COVID-19)
Burns
Inhalation injury (INH)
Artificial intelligence (AI)
Machine learning
Gradient boosting-based machine learning (GBM)
Bronchoscopy

ABSTRACT

Background: The coronavirus disease pandemic has had a tangible impact on bronchoscopy for burn inpatients due to isolation and triage measures. We utilised the machine-learning approach to identify risk factors for predicting mild and severe inhalation injury and whether patients with burns experienced inhalation injury. We also examined the ability of two dichotomous models to predict clinical outcomes including mortality, pneumonia, and duration of hospitalisation.

Methods: A retrospective 14-year single-centre dataset of 341 intubated patients with burns with suspected inhalation injury was established. The medical data on day one of admission and bronchoscopy-diagnosed inhalation injury grade were compiled using a gradient boosting-based machine-learning algorithm to create two prediction models: model 1, mild vs. severe inhalation injury; and model 2, no inhalation injury vs. inhalation injury.

Results: The area under the curve (AUC) for model 1 was 0·883, indicating excellent discrimination. The AUC for model 2 was 0·862, indicating acceptable discrimination. In model 1, the incidence of pneumonia ($P < 0{\cdot}001$) and mortality rate ($P < 0{\cdot}001$), but not duration of hospitalisation ($P = 0{\cdot}1052$), were significantly higher in patients with severe inhalation injury. In model 2, the incidence of pneumonia ($P < 0{\cdot}001$), mortality ($P < 0{\cdot}001$), and duration of hospitalisation ($P = 0{\cdot}021$) were significantly higher in patients with inhalation injury.

Conclusions: We developed the first machine-learning tool for differentiating between mild and severe inhalation injury, and the absence/presence of inhalation injury in patients with burns, which is helpful when bronchoscopy is not available immediately. The dichotomous classification predicted by both models was associated with the clinical outcomes.

* Correspondence to: Department of Plastic and Reconstructive Surgery, Chang Gung Memorial Hospital, Linkuo 5, Fu-Hsin Street, Kwei-Shan, Taoyuan 333, Taiwan.

E-mail address: firepigtw@gmail.com (H.-C. Chen).

https://doi.org/10.1016/j.burns.2023.03.011
0305-4179/

Please cite this article as: S.-Y. Yang, C.-J. Huang, C.-I. Yen et al., Machine learning approach for predicting inhalation injury in patients with burns, Burns, https://doi.org/10.1016/j.burns.2023.03.011

1. Introduction

Severe inhalation injury can lead to frequent detrimental pulmonary and systemic sequelae are in patients with burns. Unsurprisingly, the mortality associated with burn injuries increases by approximately 20% in the presence of inhalation injury [1,2]. Currently, several clinicians are inclined to assess possible inhalation injuries in patients with burns by identifying the burn injuries on the face and neck, extensive cutaneous burns, singed nasal hair, carbonaceous sputum, dysphonia, and prolonged entrapment in enclosed spaces [3,4]. Nevertheless, fibre-optic bronchoscopy is the gold standard for the diagnosis of inhalation injury [1,4,5]. Based on the Abbreviated Injury Score (AIS) criteria first proposed by Endorf and Gamelli in 2007, the patient's inhalation injury was graded on a scale ranging from 0, 1, 2, 3 and 4 by direct visualisation of mucosal injury via initial bronchoscopy (Table 1) [5]. Bronchoscopic results and the respective scoring systems provide qualitative rather than quantitative measures for patients with burns with suspected inhalation injury. While quantitative bronchoscopic stratification of inhalation injury remains to be established, it may hamper the formulation of a timely and effective treatment plan [2,3]. Furthermore, whether the AIS grade can be regarded as a primary predictor of a patient's clinical outcomes is still under debate [6,7].

Performing bronchoscopy to assess possible inhalation injury in patients with burns in the emergency department seems to be against the principle of parsimony in exploiting medical resources and practising consultation medicine. These concerns have manifested especially since the coronavirus disease (COVID-19) outbreak in 2020. After the COVID-19 outbreak, local medical centres and hospitals were required to implement isolation and triage measures. Since bronchoscopy and consultation-related resources were allocated as measures in response to the outbreak, patients with burns were less likely to have immediate access to bronchoscopy examinations compared to the pre-pandemic era. When bronchoscopy and consultation-intensive diagnoses are not available, local burns clinicians advise searching for ostensibly obvious features in patients with burns to differentiate between mild and severe inhalation injury.

Artificial intelligence (AI) is a rapidly expanding prominent academic avenue, which has produced significant results. Thus, a gradient boosting-based machine learning (GBM) method was used to first establish two dichotomous prediction models (mild vs. severe inhalation injury and no inhalation injury vs. inhalation injury) for patients with burns, followed by the identification of the respective risk factors in this study. In addition, we examined the ability of the two dichotomous models to predict the clinical outcomes of patients, including mortality, pneumonia, and duration of hospitalisation.

2. Methods

This study was reviewed and approved by the institutional review board. A 14-year (January 2007 to-June 2021), single-centre, retrospective dataset of 341 patients with burns who underwent bronchoscopy examination with inhalation injury grading was established. Patients with burns who were intubated with suspected inhalation injury and underwent fibre-optic bronchoscopy after admission were included in this study. Patients with burns who did not undergo bronchoscopy examination at initial admission were excluded from this dataset. Patients' demographic data (age, sex), vital signs (Glasgow Coma Scale, systolic and diastolic blood pressure, body temperature, and respiratory and heart rates), clinical history (smoke inhalation history, prolonged entrapment in an enclosed space), clinical symptoms and signs (hoarseness, stridor, wheezing, dyspnoea, facial or neck burn, singed nasal vibrissae, soot in the upper airway, carbonaceous sputum, total burn surface area, and burn depth), laboratory data (ratio of partial pressure of arterial oxygen to inhaled fraction of oxygen, carboxyhaemoglobin and oxyhaemoglobin fraction at admission), clinical outcomes (mortality, pneumonia, and duration of hospitalisation in days), bronchoscopy examination, and respective inhalation injury grade were extracted from the medical records. The AIS scale was adopted at the beginning of the study period. All the inhalation injury grading was provided by chest physicians at the time of bronchoscopy examinations.

The medical data on the first day of admission and bronchoscopy-diagnosed inhalation injury grade (ground truth) were compiled using the GBM algorithm to create two

Table 1 – Bronchoscopic criteria used to grade inhalation injury.

Injury Grade	Description in signs and symptoms
Grade 0 (No injury)	Absence of carbonaceous deposits, erythema, edema, bronchorrhea, or obstruction
Grade 1 (Mild injury)	Minor or patchy areas of erythema, carbonaceous deposits in proximal or distal bronchi (any or combination)
Grade 2 (Moderate injury)	Moderate degree of erythema, carbonaceous deposits, bronchorrhea, with or without compromise of the bronchi (Any or combination)
Grade 3 (Severe injury)	Severe inflammation with friability, copious carbonaceous deposits, bronchorrhea, bronchial obstruction (any or combination)
Grade 4 (Massive injury)	Evidence of mucosal sloughing, necrosis, endoluminal obliteration (any or combination)

Table 2 – Input features preprocessed for two gradient boosting-based machine learning (GBM) models.

Feature	Original Value	Model Input	Input type
All numeric features[a]	Numeric value	original value	Numeric
All binary features[b]	N	0	Categorical
	Y	1	
Sex	Male	0	Categorical
	Female	1	
Exposure type	Flame	0	Categorical
	Chemical	1	
	Thermal	2	
	Flame, Contact Thermal	3	
	Smoke	4	
	Electric	5	
PF ratio	> 300	0	Categorical
	200–300	1	
	100–200	2	
	< 100	3	
BT at triage	< 35	0	Categorical
	35–37.5	1	
	> 37.5	2	
Burn depth	0	0	Numeric
	1	1	
	2	2	
	3	3	
	1, 2	1.5	
	2, 3	2.5	
	3, 4	3.5	

[a] Numeric features include vital signs (Glasgow Coma Scale, systolic blood pressure, diastolic blood pressure, body temperature, respiratory rate, heart rate, and total burn surface area (TBSA)), and lab datum (ratio of partial pressure of arterial oxygen to inhaled fraction of oxygen, admission carboxyhemoglobin and oxyhemoglobin fraction).

[b] Binary features include clinical histories (smoke inhalation history, prolonged entrapment in enclosed space), and clinical symptoms and signs (hoarseness, stridor, wheezing, dyspnea, facial or neck burn, signed nasal vibrissae, soot in upper airway, carbonaceous sputum).

dichotomous prediction models (mild vs. severe inhalation injury and no inhalation injury vs. inhalation injury). The training group comprised 80% of patients, while the validation and test groups each included 10% of patients.

3. Input features

The input features for the two GBM models were pre-processed to model the inputs, as shown in Table 2. Missing values were handled using multiple imputation with Light GBM, which predicts missing data using the other variables in the dataset [8].

4. Model

The AI model was based on GBM learning [9], which is an additive model with a forward stage-wise boosting algorithm. This algorithm aims to build a new regression tree, which learns based on the current residual and adds it to a previous tree sequentially, without adjusting the parameters of those

Table 3 – The validation and test results of two training models.

Metrics	Model 1		Model 2	
	Mild	Severe	No inhalation injury	inhalation injury
	Inhalation injury grade 0–1	Inhalation injury grade 2–4	Inhalation injury grade 0	Inhalation injury grade 1–4
	Validation	Test	Validation	Test
AUC	0.976	0.883	0.833	0.862
Accuracy	0.914	0.838	0.885	0.806
Recall (Sensitivity)	0.933	0.777	0.906	0.827
Specificity	0.9	0.863	0.666	0.5
Precision	0.875	0.7	0.966	0.96
F1 score	0.903	0.736	0.935	0.888

Table 4 – The confusion matrix derived from test data of Model 1.

Model 1		True label	
		Mild Inhalation injury	Severe Inhalation injury
Predict	Mild inhalation injury	19	3
	Severe inhalation injury	2	7

Table 5 – Confusion matrix derived from test data of Model 2.

Model 2		True label	
		No inhalation injury	Inhalation injury
Predict	No inhalation injury	1	1
	Inhalation injury	5	24

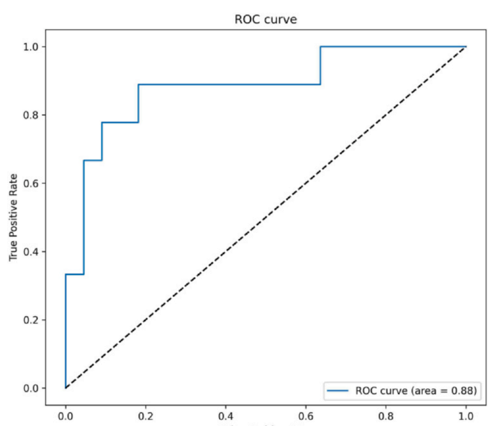

Fig. 1 – Receiver operating characteristic (ROC) of model 1.

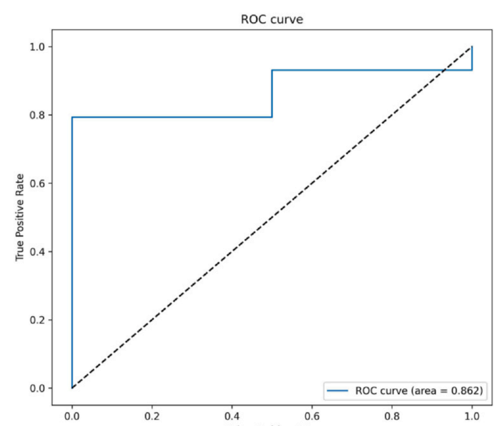

Fig. 2 – Receiver operating characteristic (ROC) of model 2.

that have already been added. Our model conformed to the algorithms specified by Friedman (2001), as shown in Algorithm 1 [9].

Briefly, logistic regression was adopted to determine the algorithms for all tree nodes, with $y_k \in \{0,1\}$, where k refers to the class and $p_k(x) = \Pr(y_k = 1)x)$, defining the function $f_k(x)$ as

$$f_k(x) = \log p_k(x) - \frac{1}{K}\sum_{l=1}^{K} \log p_l(x)$$

or equivalent to.

$p_k(x) = \frac{e^{f_k(x)}}{\sum_{l=1}^{K} e^{f_l(x)}}$ loss function was deviance loss

$L(y_k, f_k(x)) = -y_k \log p_k(x)$

The negative gradient of loss with respect to current output can be computed using the following formula.

$$-\frac{\partial L(y_{ik}, f_k(x_i))}{\partial f_k(x_i)} = y_{ik} - p_k(x_i)$$

A new regression tree m with the negative gradient $\tilde{y_{ik}} = y_{ik} - p_k(x_i)$was fitted as the target, yielding the J_m-terminal node tree with regionsR_{jkm}, $j = 1, 2, \ldots, J_m$, and γ_{jkm} was computed using the Newton–Raphson algorithm to minimise loss.

$$\gamma_{jkm} = arg\min_{\gamma_{jk}} \sum_{i=1}^{N}\sum_{k=1}^{K} L\left(y_{ik}, f_k(x_i) + \sum_{j=1}^{J} \gamma_{jk} I(x_i \in R_{jm})\right)$$

$$= \frac{K-1}{K}\frac{\sum_{x_i \in R_{jkm}} \tilde{y_{ik}}}{\sum_{x_i \in R_{jkm}} |\tilde{y_{ik}}|(1 - |\tilde{y_{ik}}|)}$$

A new regression tree was added to the previous tree to improve performance.

Algorithm 1. Gradient Boosting Machine Algorithm.

Initialize $f_0(x) = \arg\min_{\gamma} \sum_{i=1}^{N} L(y_i, \gamma)$

For $m = 1\ to\ M$:

1. $$p_k(x) = \frac{e^{f_k(x)}}{\sum_{l=1}^{K} e^{f_l(x)}}$$

2. For $k = 1\ to\ K$:

   (a) Update targets

   $$\widetilde{y_{ik}} = y_{ik} - p_k(x_i), \qquad i = 1,2,\ldots,N$$

   (b) Fit a regression tree to the targets $\widetilde{y_{ik}}$, yielding the J_m-*terminal node tree* with regions R_{jkm}, $j = 1,2,\ldots,J_m$

   (c) Compute γ_{jkm}

   $$\gamma_{jkm} = \frac{K-1}{K} \frac{\sum_{x_i \in R_{jkm}} \widetilde{y_{ik}}}{\sum_{x_i \in R_{jkm}} |\widetilde{y_{ik}}|\,(1 - |\widetilde{y_{ik}}|)}$$

   (d) Update $f_m(x)$

   $$f_{km}(x) = f_{km}(x) + \sum_{j=1}^{J} \gamma_{jkm} I(x \in R_{jkm})$$

Output $f_k(x)$

$$f_k(x) = f_{kM}(x), k = 1,2,\ldots,K$$

M: number of regression trees
K: number of classes
N: number of samples

Thereafter, two injury grade-based dichotomous prediction models were developed (Table 3).

In model 1 (mild vs. severe), patients with grade 0 and 1 inhalation injury were classified into the mild group and patients with grade 2, 3, and 4 inhalation injury were classified into the severe group.

In model 2 (no inhalation injury vs. inhalation injury), patients with burns with grade 0 inhalation injury were designated as having no inhalation injury, whereas patients with grade 1, 2, 3, and 4 inhalation injuries were designated as having inhalation injury.

After prediction model generation, we attempted to identify the model-specific risk factors (feature importance) contributing towards the prediction of patients' dichotomous injury grades. Step one entailed choosing a feature and randomly shuffling its value. Step two involved calculating the prediction score using a shuffled dataset. Step three entailed calculating the difference between the prediction score and baseline, yielding the importance of this feature.

Inhalation injuries may predispose patients to pneumonia. Moreover, inhalation injury and pneumonia may have significant additive effects on burn mortality and prolonged admission. We further analysed the prevalence of pneumonia, the mortality rate, and duration of hospitalisation between the dichotomised groups and assessed whether the dichotomous models could predict patients' clinical outcomes.

Statistical analyses were performed using IBM SPSS Statistics version 26. All data were presented as the mean ± standard deviation. Analyses were performed using McNemar's test. Statistical significance was set at $p < 0.05$.

5. Role of the funding source

None.

6. Results

This study included 341 patients with burn injuries. In this dataset, the patients' mean ± standard deviation age was 40·9 ± 16·4 years (range: 1–91 years)·The average total body surface area of burns (TBSA) was 23·3% ± 24·9%. The average duration of hospitalization and ventilator use were 30·3 ± 30·0 and 10·4 ± 12·6 days, respectively. The mortality rate was 10·0%. Following bronchoscopic examination and AIS-based inhalation injury diagnosis, 22 patients were classified as grade 0 (6·5%), 198 patients as grade 1 (58·1%), 83 patients as grade 2 (24·3%), 28 patients as grade 3 (8·2%), and 10 patients as grade 4 (2·9%).

The validation and test results of the two AI models and their evaluation metrics derived from the test data are enumerated in Tables 3–5. Both models were tested on 31 test datasets, after being trained on 275 training datasets and verified using 35 validation datasets. Fig. 1 shows the receiver operating characteristic (ROC) curve of model 1; the area under the curve (AUC) for this model was 0·883, which indicates excellent discrimination. Model 1 had the following performance scores: recall (sensitivity) = 0·777, specificity = 0·863, F1 score = 0·736, accuracy = 0·838, and precision = 0·7. Fig. 2 shows the ROC curve of model 2; the AUC for this model was 0·862, indicating excellent discrimination. The performance scores for model 2 were as follows: recall (sensitivity) = 0·827, specificity = 0·5, F1 score = 0·888, accuracy = 0·806, and precision = 0·96 (Table 3).

After prediction model generation, the feature importance for dichotomous prediction was obtained. The feature importance summation of all risk factors was designated as 100%. The top five risk factors that contributed to distinguishing between mild and severe inhalation injury in model 1 were subjective inhalation reminiscence (28·9%), soot in the upper airway (14·5%), burn injury occurring in an enclosed space (14%), elevated carboxyhaemoglobin (COHB) level (13·2%), and singed nasal vibrissae (6·1%). "Subjective inhalation reminiscence" means that patients thought they had inhaled hot air at the fire scene. These data were obtained from patients themselves. 87 patients were intubated before arrival at our emergency department. To find out if these patients had inhaled hot air, we either had to wait until these patients were conscious or ask their families/friends whether they had reported it before being intubated. (Fig. 3). The top five risk factors of model 2 were singed nasal vibrissae (18·6%), soot in the upper airway (12.2%), burn depth (11·3%), systolic blood pressure (sBP) at triage (10·7%), and elevated COHB level (7·5%). The artificial intelligence software will consider each feature. Although the top five features suggest that they are the ones that help make predictions the most, this does not mean that other features are not important. More features improve the algorithm's performance. In our decision tree model, multiple trees were constructed to determine the predictors that influence the target outcome. Through analysis, we identified several trees that utilized COHB, burn depth, and systolic blood pressure at triage as key variables for evaluating the target outcome. Specifically, we established threshold values of 1.55 for COHB, 130.55 mmHg for systolic blood pressure at triage, and second degree burn for burn depth. These threshold values were utilized to partition the predictor variables into binary groups and create decision nodes in the decision tree, enabling the identification of high-risk patients. (Fig. 4).

We further evaluated whether the dichotomous classification (mild vs. severe inhalation injury and no inhalation injury vs. inhalation injury) predicted by the two AI models was associated with the subsequent clinical outcomes.

In model 1, patients with severe inhalation injury showed statistically significant trends toward a higher incidence of pneumonia ($P < 0·001$) and higher mortality rate ($P < 0·001$), albeit without significant differences in the duration of hospitalization (days) ($P = 0·1052$). No significant differences were observed in the percentage of TBSA burns between the mild and severe inhalation injury groups ($P = 0·9021$). The proportion of men ($P < 0·001$) and older individuals ($P = 0·0328$) was predominantly higher in the severe inhalation injury group (Table 6).

In model 2, patients with inhalation injury displayed statistically significant trends towards a higher incidence of pneumonia ($P < 0·001$), mortality ($P < 0·001$), and duration of hospitalisation ($P = 0·021$). There were no significant differences in age between the inhalation injury and non-inhalation injury groups. The proportion of men ($P < 0·001$) and higher percentage of TBSA burns ($P = 0·0124$) were predominantly higher in the inhalation injury group (Table 7).

7. Discussion

An accurate and quick diagnosis of inhalation injury and its severity are needed in patients with burns for subsequent treatment and prognostic evaluation. Most medical institutions had adopted isolation and triage measures in response to the challenging circumstances of the global novel coronary

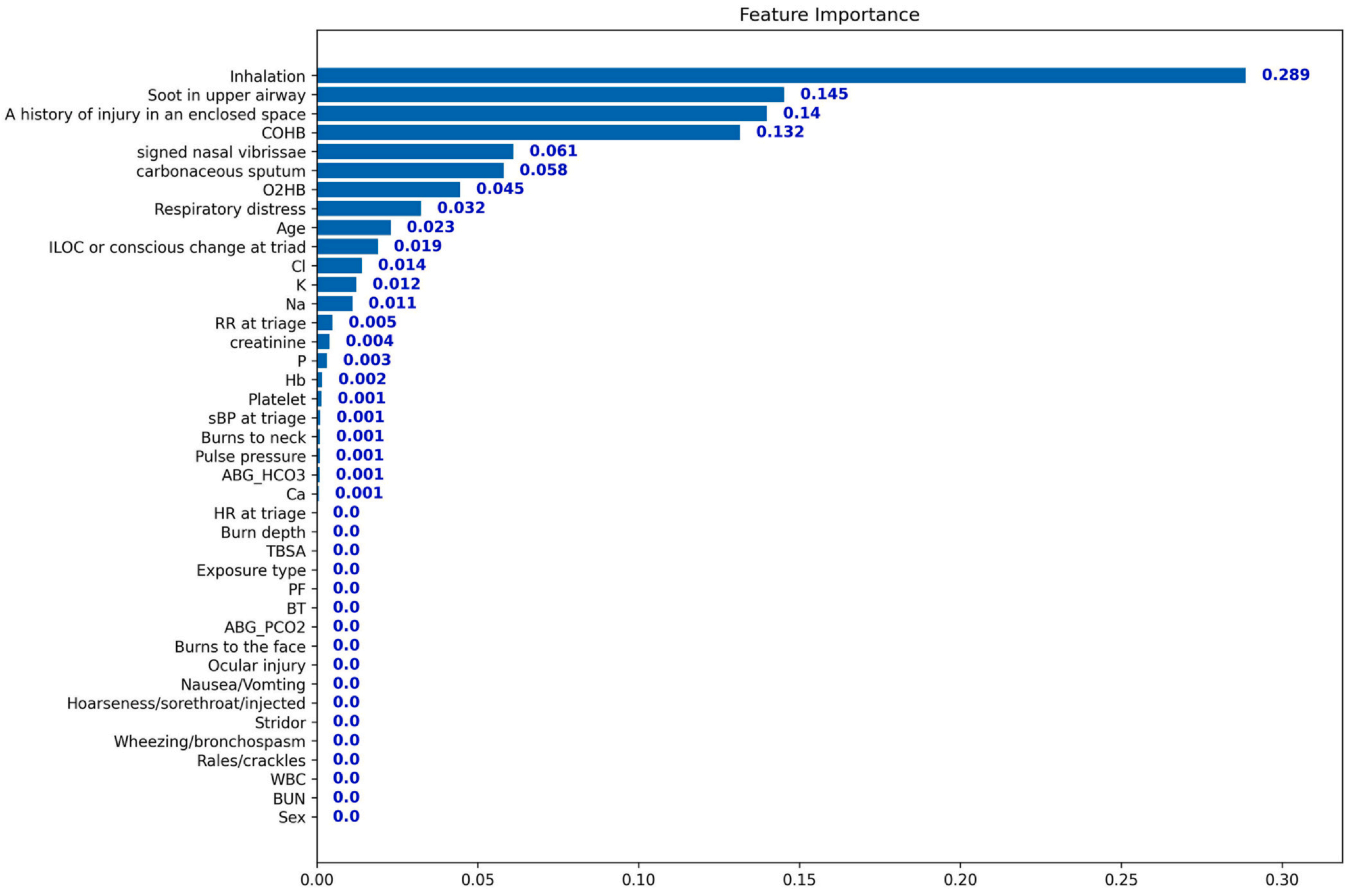

Fig. 3 – Feature importance of model 1.

pneumonia (COVID-19) epidemic. As a result, it became more challenging to promptly schedule bronchoscopy examinations for patients with burns, which affected decision-making regarding medical treatments and prognostication.

AI has developed rapidly in recent years, and numerous related studies have been conducted in the field of burn injury and treatment [11–14]. To the best of our knowledge, this is the first study to apply a machine-learning approach to predict inhalation injury in patients with burns. We developed two AI inhalation injury prediction models that can predict mild and severe inhalation injury (model 1) as well as the absence or presence of inhalation injury (model 2), based on the bronchoscopic diagnosis data of patients with burns. After the development of each prediction model, we

Table 6 – The dichotomous classification in relation to clinical outcomes (incidence of pneumonia, mortality rate, admission days), gender, age and TBSA in model 1.

Characteristics of the study population			
Variable	Mild inhalation injury	Severe inhalation injury	Mcnemar Test P value
Pneumonia, N (%)	33 (15%)	65 (55%)	< 0.001*
No pneumonia, N (%)[a]	187 (85%)	52 (45%)	
Survival, N (%)	202 (91.8%)	105 (86.8%)	< 0.001*
Mortality, N (%)	18 (8.2%)	16 (13.2%)	
Admission days, average (range)	28.2590 (1–127)	33.7520 (3–216)	0.1052
Female (%)	58 (26.4%)	43 (35.5%)	< 0.001*
Male (%)	162 (73.6%)	78 (64.5%)	
Age (range)	39.536 (1–91)	43.487 (6–85)	0.0328*
TBSA, average (range)	23.388 (0–100)	23.041 (0–100)	0.9021

TBSA: total body surface area

[a] : Four cases of data loss in the “No pneumonia” group
* p < 0.05 considered statistically significant.

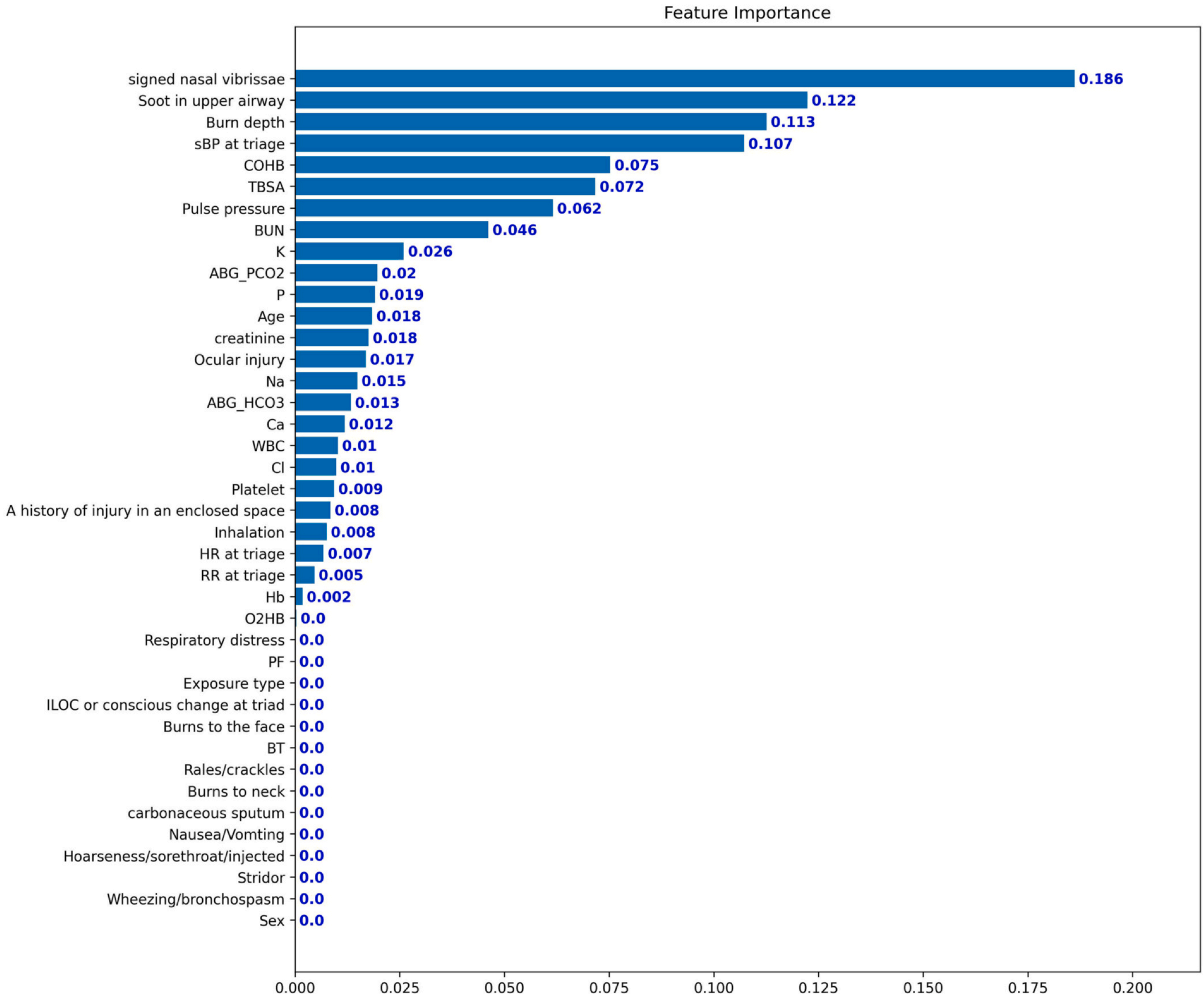

Fig. 4 – Feature importance of model 2.

identified the top five risk factors in each model, which could aid physicians in assessing the absence/presence and severity of inhalation injury in patients with burns in the emergency room. The clinical outcomes, viz. patient mortality, pneumonia, and duration of hospitalisation (in days) were associated with dichotomous prediction models.

The performance of model 1 was satisfactory. It could excellently discriminate between mild and severe inhalation injury, and severe inhalation injury was found to be associated with a higher incidence of pneumonia and mortality rate. Model 2 had low specificity and acceptable discrimination. The reason for this is that only a small number of patients (22 out of 341) with grade 0 inhalation injury were included in this study. Therefore, this model and the associated risk variables may not be sufficient to help clinicians decide whether to intubate patients with burns with suspected inhalation injury. More patients without inhalation injury should be included to enhance the performance of model 2 in the future. In this study, the top risk factors of model 2 was singed nasal vibrissae (18·6%). Despite the emerging belief among certain experts that inhalation injury cannot be accurately predicted by singed nasal hairs [15], numerous previous publications imply that it may still support the inhalation injury diagnosis [16–19]. A burn to the face or neck, however, had a very minor impact on helping make predictions. According to our research, numerous victims with inhalation injury had no burn injuries on their faces. I believe this is why "burn the face or neck" had such a negligible effect on the prediction of inhalation injury in our AI model. In our upcoming study, we will consider the combined risk factor for third degree facial burns.

We attempted to train the AI model to recognise five classifications (AIS scores of 0, 1, 2, 3 and 4), but the accuracy of the prediction was quite poor. The reason for this could be that, after being classified into five groups, the number of cases in each was too small and uneven.

Table 7 – The dichotomous classification in relation to clinical outcomes (incidence of pneumonia, mortality rate, admission days), gender, age and TBSA in model 2.

Characteristics of the study population			
Variable	No inhalation injury	Inhalation injury	Mcnemar Test P value
Pneumonia, N (%)	0 (0%)	98 (55%)	< 0.001*
No Pneumonia, N (%)[a]	22 (100%)	217 (45%)	
Survival, N (%)	22 (100%)	285 (89.3%)	< 0.001*
Mortality, N (%)	0 (0%)	34 (10.7%)	
Admission days, average (range)	16.045 (1–73)	31.184 (1–216)	0.021*
Female (%)	4 (18.18%)	97 (30.4%)	< 0.001*
Male (%)	18 (81.82%)	222 (69.6%)	
Age (range)	34.5454 (1–62)	41.379 (2–91)	0.058
TBSA, average (range)	10.454 (0–70)	24.148 (0–100)	0.0124*

TBSA: total body surface area

[a] : Four cases of data loss in the "No pneumonia" group
* $p < 0.05$ considered statistically significant.

It may be possible to anticipate clinical outcomes by grading the severity of the acutely damaged tracheobronchial mucosa. However, bronchoscopy permits qualitative rather than quantitative assessment, and whether AIS grade should be considered a key indicator of a patient's clinical results remains controversial [6,7]. Although bronchoscopy is typically regarded as a safe procedure, it is invasive and uncomfortable. The potential side effects of bronchoscopy include bleeding, infection, pneumothorax, heart, or lung failure.etc [20]. Sedation is widely used to relieve discomfort during bronchoscopy, but it also has certain complications, such as low blood pressure, respiratory issues, and allergic reactions.

According to the American Lung Association, the estimated cost of bronchoscopy is between $800 and $2000 dollars, depending on the type of bronchoscopy performed and the location of the medical facility. However, the cost of machine learning hardware and software for medical applications can also vary based on several factors, such as the complexity of the software, the type of hardware required, and the level of customization required for the specific medical application. In extreme cases, the cost of the hardware and software for machine learning could reach several hundred thousand dollars. The initial cost of investing in machine learning software or hardware may be higher in the context of a hospital or medical practice, but there can be a considerable return on investment in the form of better patient care and more noninvasive medical procedures.

During bronchoscopy, the airway is directly visible, inhaled dust can be irrigated and cleaned, allowing for the collection of samples for microbiological cultures. While the machine learning algorithm can assist clinicians with inhalation injury diagnosis, it cannot completely replace bronchoscopy, which provides not only diagnosis but also treatment (irrigation and suction of the dust) and further follow-up. Even so, the two AI models could facilitate noninvasive and quick determination of patients' inhalation injury diagnosis, treatment, prognosis, and risk assessment in areas with insufficient medical resources and manpower, or when bronchoscopy cannot be scheduled quickly. This is beneficial and can assist clinicians in evaluating patients with burns in the emergency room for inhalation injury diagnosis. Medical centres worldwide can train similar models based on their medical data and bronchoscopy diagnoses in the same manner.

8. Limitations

This study has some limitations. Due to the retrospective nature of this study, some data might have been missing or incomplete. The results could have been improved with the inclusion of additional data and more balanced distribution. Increasing the amount of training data by gathering information from numerous medical facilities can improve the performance of our AI models. However, it is challenging to establish a single institution accepted gold standard method of assessment because each hospital has different bronchoscopy equipment and physicians.

9. Conclusions

We developed the first machine learning approach for differentiating between mild and severe inhalation injury as well as the presence of absence of inhalation injury in patients with burns, which could be helpful when bronchoscopy examination is not immediately available. The dichotomous classification predicted by the two models was associated with the subsequent clinical outcomes. We also provided the top five important risk factors for assisting clinicians with quick decision-making in the emergency department.

Role of the funding source

None.

Disclosure

The authors do not have any commercial associations or financial relationships that might pose or create conflicts of interest with the information presented.

Acknowledgements

We are extremely grateful to Dr. Anna E. Yu, M.D., for her immense contribution and assistance with this research.

Conflicts of interest

The authors have no conflicts of interest to declare.

REFERENCES

[1] Shirani KZ, Pruitt Jr BA, Mason Jr. AD. The influence of inhalation injury and pneumonia on burn mortality. Ann Surg 1987;205:82–7. https://doi.org/10.1097/00000658-198701000-00015
[2] Dries DJ, Endorf FW. Inhalation injury: epidemiology, pathology, treatment strategies. Scand J Trauma Resusc Emerg Med 2013;21:31. https://doi.org/10.1186/1757-7241-21-31
[3] Dyamenahalli K, Garg G, Shupp JW, Kuprys PV, Choudhry MA, Kovacs EJ. Inhalation injury: unmet clinical needs and future research. J Burn Care Res 2019;40:570–84. https://doi.org/10.1093/jbcr/irz055
[4] Deutsch CJ, Tan A, Smailes S, Dziewulski P. The diagnosis and management of inhalation injury: an evidence based approach. Burns 2018;44:1040–51. https://doi.org/10.1016/j.burns.2017.11.013
[5] Endorf FW, Gamelli RL. Inhalation injury, pulmonary perturbations, and fluid resuscitation. J Burn Care Res 2007;28:80–3. https://doi.org/10.1097/BCR.0B013E31802C889F
[6] Albright JM, Davis CS, Bird MD, et al. The acute pulmonary inflammatory response to the graded severity of smoke inhalation injury. Crit Care Med 2012;40:1113–21. https://doi.org/10.1097/CCM.0b013e3182374a67
[7] Spano S, Hanna S, Li Z, Wood D, Cartotto R. Does bronchoscopic evaluation of inhalation injury severity predict outcome? J Burn Care Res 2016;37:1–11. https://doi.org/10.1097/BCR.0000000000000320
[8] Van Buuren S, Groothuis-Oudshoorn K. MICE: multivariate imputation by chained equations in R. J Stat Softw 2011;45:1–67. https://doi.org/10.18637/jss.v045.i03
[9] Friedman J. Greedy function approximation: a gradient boosting machine. Ann Stat 2001;29:1189–232. Retrieved July 9, 2021 from ⟨http://www.jstor.org/stable/2699986⟩.
[11] Chang CW, Lai F, Christian M, et al. Deep learning–assisted burn wound diagnosis: diagnostic model development study. JMIR Med Inf 2021;9:e22798.
[12] E Moura FS, Amin K, Ekwobi C. Artificial intelligence in the management and treatment of burns: a systematic review. Burns Trauma 2021;9:tkab022.
[13] Huang S, Dang J, Sheckter CC, Yenikomshian HA, Gillenwater J. A systematic review of machine learning and automation in burn wound evaluation: a promising but developing frontier. Burns 2021;47:1691–704.
[14] Fransén J, Lundin J, Fredén F, Huss F. A proof-of-concept study on mortality prediction with machine learning algorithms using burn intensive care data. Scars Burn Heal 2022;8. 20595131211066585.
[15] Desai Suneel Ramesh, Zeng Delong, Chong Si Jack. Airway management in inhalation injury: a case series. Singap Med J 2020;61(1):46–53.
[16] McCall JE, Cahill TJ. Respiratory care of the burn patient. J Burn Care Rehabil 2005;26:200–6.
[17] Palmieri TL. Inhalation injury: research progress and needs. J Burn Care Res 2007;28:549–54.
[18] Woodson LC. Diagnosis and grading of inhalation injury. J Burn Care Res 2009;30:143–5.
[19] Palmieri TL, Gamelli RL. Diagnosis and Management of Inhalation Injury (Acute Burn Care). Handbook of Burns Volume 1. New York: Springer; 2012. p. 163–72. (Acute Burn Care).
[20] Du Rand IA, Blaikley J, Booton R, Chaudhuri N, Gupta V, Khalid S, Mandal S, Martin J, Mills J, Navani N, Rahman NM. British thoracic society guideline for diagnostic flexible bronchoscopy in adults: accredited by NICE. Thorax 2013;68(Suppl 1):i1–44.