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ORIGINAL ARTICLE

Machine Learning Models for Predicting In-Hospital Mortality and Pressure Ulcer Development following Traumatic Spinal Cord Injury; A Cross-sectional Study

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Abstract: **Introduction:** Traumatic spinal cord injury (TSCI) remains a significant cause of long-term disability, with mortality and pressure ulcer (PU) development being key determinants of patient outcomes. This study aimed to develop and interpret machine learning (ML) models for predicting in-hospital mortality and PU formation in TSCI patients using data from the National Spinal Cord Injury Registry of Iran (NSCIR-IR). **Methods:** Patients with TSCI admitted between 2015 and 2023 were included in the analysis. Data preprocessing included iterative imputation, feature selection with cross-validation, and class balancing using SMOTE. Nine ML algorithms were trained and validated on an 80:20 split dataset. Model performance was assessed using the area under the receiver operating characteristic curve (AUC) and other standard metrics. Feature importance and interpretability were evaluated using permutation importance and Shapley Additive Explanations (SHAP) analysis. **Results:** A total of 499 patients were included. The LightGBM classifier achieved the highest performance in mortality prediction (AUC = 0.85; 95% CI: 0.73-0.94), followed by KNN and Naive Bayes. For PU prediction, the Random Forest model performed best (AUC = 0.83; 95% CI: 0.72-0.93), outperforming XGBoost and LightGBM. Ventilator use, ASIA grade, and sensory and motor scores were the strongest predictors of mortality, while first aid given, ventilator use, and the number of injured vertebrae were the strongest predictors of PU risk. SHAP analysis confirmed these findings. **Conclusion:** ML algorithms can accurately identify TSCI patients at high risk of mortality and PU development using routinely collected clinical data. Integrating such interpretable ML tools into early triage systems could enable timely preventive interventions and improve patient outcomes.

Keywords: Spinal Cord Injuries; Machine Learning; Mortality; Pressure Ulcer

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1. Introduction

Traumatic spinal cord injury (TSCI) is a serious neurological condition that leads to lifelong disability, secondary complications, and a high economic burden (1). Globally, the incidence of TSCI ranges from 10 to 83 cases per million population annually (2), with mortality rates remaining considerable despite advances in acute care. In low- and middle-income countries, including Iran, the epidemiology of TSCI reflects a younger population at risk, a predominance of traffic-related injuries, and limited rehabilitation resources (3). In-hospital mortality and pressure ulcer (PU) development are among the most serious complications of TSCI. Notably, PU contributes substantially to prolonged hospitalization, readmission, and reduced quality of life (4). Identifying patients at higher risk for these outcomes remains a clinical priority, as timely intervention could mitigate morbidity and improve long-term survival (5).

The level and completeness of injury, respiratory compromise, and associated trauma primarily determine mortality following TSCI. Ventilator dependence, hemodynamic instability, and severe cervical injuries are well-established predictors of poor survival (6). Conversely, PUs develop due to sustained immobility, impaired sensation, and inadequate acute or rehabilitative care (4). PUs are not only a marker of poor inpatient management but also increase the risk of sepsis and mortality (7). Traditional statistical approaches have provided valuable insights into individual risk factors, but their ability to handle the complex, non-linear interactions between numerous clinical variables remains limited.

Recent advances in artificial intelligence (AI) and machine learning (ML) offer an opportunity to overcome these challenges. ML models can process large, multidimensional datasets and automatically capture subtle patterns that conventional regression analyses may miss. They have shown promise in predicting outcomes such as mortality, infection, and functional recovery across diverse neurological and critical-care settings (8). However, limited studies have focused on

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applying ML to TSCI populations, particularly in middle-income countries where data are scarce, and management protocols vary widely.

The National Spinal Cord Injury Registry of Iran (NSCIR-IR) provides a multicenter dataset for developing such predictive models. By using its clinical, demographic, and injury-related variables, ML algorithms can help physicians identify high-risk patients early in their hospital course. Therefore, this study aimed to employ a broad range of ML models to (1) predict in-hospital mortality and PU formation among TSCI patients, (2) compare model performance across algorithms, and (3) determine the most influential predictors contributing to each outcome through interpretable ML techniques.

2. Methods

2.1. *Study design and setting*

This retrospective cross-sectional study utilized data from the NSCIR-IR. The NSCIR-IR is a dataset designed to collect and analyze data on individuals with TSCI in Iran. The registry aims to improve the quality of care, understand epidemiological trends, and facilitate research on SCI. The NSCIR-IR collects demographic information, injury characteristics, clinical assessments, treatment details, and patient outcomes. The definition of the variables used in this study is presented in the Supplementary Material. The registry includes data from ten hospitals in eight cities and includes patients with traumatic spinal fractures with or without spinal cord injuries since 2015. The main aim of this study was predicting the in-hospital mortality and PU development following TSCI. Analyses were conducted on patients with TSCI who had available data for either mortality or PU status. Ethical approval for the study was obtained from Tehran University of Medical Sciences IR.TUMS.SINAHOSPITAL.REC.1404.048.

2.2. *Data preprocessing*

Variables with missing values that could not be reliably imputed, those with a single constant value, and those with over 95% of entries having the same value were omitted to avoid unreliable results. Additionally, similar categories were combined when they were either very similar or accounted for a very low proportion. Feature correlations were computed to assess redundancy, and highly correlated features were removed. After this initial cleaning, data preprocessing was conducted using a pipeline that included scalers, encoders, feature selectors, imbalance handlers, and estimators.

Missing data was managed using a custom iterative imputer that extended Scikit-learn's framework. Continuous variables were imputed iteratively using Lasso regression, while categorical variables were addressed using logistic regression with an L1 norm. Categorical variables, such as injury type and ASIA scores, were encoded using one-hot encoding for nominal data, whereas ordered data, including education levels, were encoded using ordinal encoding. Continuous variables were standardized using z-score scaling. An automated feature selection process was implemented to identify the most relevant predictors. Using Recursive Feature Elimination with Cross-Validation (RFECV), features were ranked by importance. Two estimators, Random Forest Classifier and Logistic Regression (LR), were tested during separate tuning sessions. Class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE), which generated synthetic samples for the minority class. For specific models, the original distribution was preserved by not applying specific balancing techniques. Performance-based decisions on the best handling approach were made during a randomized search with cross-validation.

2.3. *Machine Learning Models*

The following machine learning algorithms were employed to predict in-hospital mortality and pressure ulcer outcomes: Random Forest Classifier, XGBoost Classifier, LightGBM Classifier, Neural Networks (Multi-Layer Perceptron, Support Vector Machine, Logistic Regression, Naive Bayes Classifier, K-Nearest Neighbors (KNN), and Decision Tree Classifier). Model training and evaluation were conducted using the Scikit-learn, XGBoost, and LightGBM libraries. The pipeline underwent hyperparameter tuning via a randomized search to optimize over a defined search space.

2.4. *Evaluation metrics*

Model performance metrics included the area under the receiver operating characteristic curve (AUC), accuracy, balanced accuracy, F1-score, precision, recall, and specificity. Receiver operating characteristic (ROC) curves were also plotted to visually assess the model's discriminative ability at different thresholds. Threshold-dependent metrics (all except AUC) were calculated using a default probability threshold of 0.5 to convert predicted probabilities into binary class labels.

2.5. *Training and testing*

The dataset was split into training and test sets at 80:20. Stratified sampling ensured a proportional representation of mortality class and individuals with high missing values (more than 5). A randomized search with 5-fold stratified cross-validation was used for hyperparameter tuning. During training, AUC was monitored, and the number of iterations required for each model pipeline was determined when virtually no further performance gains were observed. The nine best models were selected, and all metrics were computed for them, including plotting ROC curves. These models were also evaluated on the test set, where all metrics were recalculated, and plots were generated to validate their performance (Supplementary Figure 1).

2.6. *Interpretation and statistical analysis*

Descriptive statistics were used to summarize baseline characteristics. Statistical associations between predictors and outcomes were evaluated using chi-square tests for categorical variables, and t-tests or Mann-Whitney U tests for continuous variables. To control for multiple comparisons and reduce the likelihood of type I errors, the Benjamini-Hochberg False Discovery Rate (FDR) procedure was applied to adjust p-values. The 95% confidence intervals for performance metrics were computed by bootstrapping with 10000 samples on the test set. Feature importance interpretation utilized Shapley Additive Explanations (SHAP) and permutation importance to assess interpretability.

2.7. *Software and tools*

Primary libraries included Pandas for data manipulation, Scikit-learn for model development and evaluation, XGBoost and LightGBM for gradient boosting, Matplotlib and Seaborn for visualization, and Joblib for efficient model saving. All the codes used in this study will be available upon request.

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3. Results

3.1. *Participants' characteristics*

After data cleaning, 499 patients with TSCI were included in this study. Of these, 399 patients were selected for the training set, and 100 for the test set. In total, 16.83% of these patients did not survive, and 14.63% developed PU. The variables, along with their distributions in each group, are summarized in Table 1. Mean age of included patients was 38.5 years (95% CI: 37.1–40.0). The mean systolic and diastolic blood pressures at admission were 113.3 mmHg and 71.1 mmHg, respectively, and the mean GCS score was 14.3 ± 1.2, showing mostly alert patients. According to the ASIA Impairment Scale, 53.0% of patients presented with grade A, while grades C and D accounted for 18.9% and 23.6%, respectively.

Regarding injury characteristics, traffic accidents (52.1%) and falls (40.3%) were the most common causes, most often occurring in car passengers (63.1%) or during work-related activities (38.7%). Cervical involvement was observed in 45.3% of cases, followed by thoracic (35.1%) and lumbar (30.5%) levels, and 22.7% of patients required ventilator support during hospitalization. First aid was administered in 18.8% of cases, and spinal immobilization was documented in 46.3%.

In terms of comparison, several significant associations were identified between variables and the outcomes of interest. Age was an important factor, with non-survivors being significantly older than survivors (45.73 (95% CI: 41.92-49.54) vs. 37.09 (95% CI: 35.61-38.56); $p < 0.001$). Complete SCI was also considerably more frequent in non-survivors (89.19% (95% CI: 82.11-96.26) vs 47.69% (95% CI: 42.74-52.65); $p < 0.001$). On the other hand, the proportion of patients receiving first aid was significantly higher in the PU group compared to the non-PU group (42.65% (95% CI: 30.89-54.40) vs 14.36% (95% CI:10.75-17.98); $p < 0.001$), and the number of injured vertebrae was significantly greater in patients with PU compared to those without (FDR = 0.005). The times from triage to admission and from injury to admission were not significantly different between the groups. The education level of survivors was significantly higher than that of non-survivors.

3.2. *Model development for predicting in-hospital mortality*

For mortality prediction, the LGBM performed best, achieving an AUC of 0.85 (95% CI: 0.73 to 0.94), followed by the KNN and Naive Bayes classifiers, which showed similar performance with only minor differences. The Decision Tree classifier showed the lowest performance with an AUC of 0.78. LGBM used 18 features for prediction (after feature encoding), while KNN used only four features and showed the least drop in AUC from test to train (0.01). All other models exhibited a more significant drop in performance, ranging from 0.06 to 0.08 (Table 2 and Figure 1A).

In the permutation importance analysis for the mortality prediction models, several features emerged as important across different machine learning algorithms. Ventilator Use consistently ranked as the most influential variable in all models, indicating its high impact on predictive performance. The Superficial Sensation Score and Proprioception Score were identified as essential features in models such as the LGBMClassifier and Random Forest. Other features that showed notable importance included the ASIA Impairment Classification, which was consistently ranked highly in models such as XGBClassifier and K-Nearest Neighbors. Age didn't show a significant impact on the model performance when shuffled. Additional variables, such as Education Level, TBI, and Motor Score, were also identified as minor contributing predictors in some models, though their impact varied across models. SHAP analysis further confirmed the importance of these features. Analysis of the top-performing models, particularly the LGBM classifier, showed ventilator use, superficial sensation score, motor score, proprioception score, age, education level, cervical injury, and ASIA impairment classification as the most influential variables. These features consistently displayed the highest mean absolute SHAP values, indicating their substantial impact on the predicted probability of mortality (Figure 1B).

3.3. *Model development for predicting pressure ulcers*

For the prediction of pressure ulcers, the Random Forest classifier performed the best with an AUC of 0.83, followed by the XGBoost classifier (AUC = 0.81) and LGBM classifier (AUC = 0.80). The Random Forest model achieved this performance with 36 features, while the XGBoost classifier used only 8. KNN showed the closest AUC to its training score (difference = 0.01) and used the fewest features, with 6. In contrast, other models exhibited much larger discrepancies in their AUC scores between training and testing, with differences ranging from 0.09 to 0.16 in either direction. Despite its minimal discrepancy, KNN did not achieve as high an AUC (0.64) as the other models (Table 3 and Figure 2A).

In the analysis of permutation importance for the pressure ulcer prediction models, several features emerged as important across different machine learning algorithms. First aid given consistently ranked as the most influential variable in all models, indicating its high impact on predictive performance. Ventilator use was frequently identified as a significant predictor, ranking among the top features in multiple models, suggesting its potential role in pressure ulcer development among TSCI patients. The number of injured vertebrae also emerged as a significant predictor in models such as the LGBMClassifier, Random Forest, and SVC, indicating the potential impact of injury severity on pressure ulcer risk. Other variables, such as age, showed moderate importance in models such as MLPClassifier and SVC, while additional predictors, including injury cause, urinary/fecal incontinence, and the presence of other pain, were also highlighted, with their relative importance varying across models. SHAP analysis of the random forest classifier revealed that the number of injured vertebrae, motor score, proprioception score, superficial sensation score, ventilator use, presence of other pain, and urinary/fecal incontinence were key contributors to the model's output (Figure 2B).

4. Discussion

In this study, we employed a wide range of ML algorithms to predict two clinically essential outcomes, mortality and PU occurrence, in patients with TSCI. Our findings show both the potential and the challenges of applying ML techniques in this population. The classification of in-hospital mortality achieved robust performance, with an AUC of 0.85, whereas predictions for PU showed somewhat lower AUCs and greater discrepancies between training and test evaluations.

Consistent with prior reports, ventilator use, ASIA Impairment Scale, and motor and sensory scores emerged as dominant predictors of mortality (8, 9). Ventilator dependence reflects the

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severity of respiratory compromise and high-level cervical injury, both well-established determinants of mortality following TSCI. In contrast, age, although associated with mortality in univariate analysis, contributed less to the model's performance when nonlinear interactions were considered, supporting the observations of Fallah et al., who found that the interplay between age, neurological severity, and injury morphology better explains mortality risk than any single factor (10).

For PU prediction, first aid administration, ventilator use, and the number of injured vertebrae were the most influential variables across models. The association between early first aid and PU likely reflects the inclusion of severely wounded or immobilized patients rather than a direct causal link. Similarly, ventilated patients and those with multiple vertebral fractures are typically immobilized longer and experience greater perfusion compromise, recognized precursors to PU formation (11). The contribution of urinary and fecal incontinence, observed in the SHAP analysis, aligns with prior clinical studies that identified these as major extrinsic risk factors for skin breakdown (12).

Our models reinforce the growing recognition that outcome prediction in TSCI cannot rely solely on linear associations. As shown in previous works by Wang et al. and Shimizu et al., integrating multidimensional clinical variables improves prognostic accuracy compared with traditional regression or scoring systems such as the Brain and Spinal Cord Injury Center (BASIC) or Spinal Cord Independence Measure (SCIM) scales (13, 14). While we focused exclusively on structured clinical data, incorporating laboratory or imaging-derived variables (e.g., magnetic resonance imaging (MRI) metrics or automated lesion quantification) could further enhance performance (15). Future research may also explore integrating these ML frameworks into clinical dashboards to support individualized risk alerts and early intervention strategies.

Notably, MRI has been shown to play an essential role in the evaluation and prognostication of SCI (15). Imaging-based indices such as the Brain and Spinal Cord Injury Center (BASIC) score have demonstrated substantial predictive value for assessing injury severity and neurological recovery, often outperforming conventional MRI measures (16). In parallel, early surgical decompression has consistently been shown to improve recovery potential and reduce secondary damage in acute SCI. It has therefore been included in some studies as a prognosis predictor (17). Future studies could benefit from including these features and comparing their performance.

Moreover, variability in outcome definitions across studies complicates direct comparisons. While some investigations evaluate discharge ASIA grade or short-term neurological recovery (18), others use 6-month ASIA improvement (13), 1-year SCIM scores (17), and mortality (10) as endpoints. These inconsistencies reflect differing clinical objectives, functional recovery versus survival, and can influence model performance and interpretability. Future studies should aim to standardize outcome measures or develop multi-endpoint frameworks to enable more consistent validation and translation of predictive models across centers and populations.

Additionally, unlike the mortality models, our efforts to forecast PU were less successful. Although random forest and gradient boosting models yielded AUCs as high as 0.83 on the test data, the test scores were often higher than the training scores, likely due to random variation stemming from the small sample size, a pattern atypical in machine learning. This discrepancy underscores the complexity of modeling PU risk, which can depend on multiple factors (e.g., mobility status, nutrition, wound care) that are not fully captured in the registry. First aid received, ventilator use, and the number of injured vertebrae repeatedly surfaced as top predictors. While ventilator use showed a similar pattern of relevance as in mortality prediction, the consistent prominence of 'first aid given' across models suggests a potential link to early care dynamics. This feature's high permutation importance suggests that it may serve as a proxy for unmeasured factors, such as delays in transfer, the adequacy of initial resuscitation efforts, or overall injury severity.

4.1. *Limitations*

Several limitations merit consideration. The modest sample size reduces the reliability of performance estimates. We addressed data imbalance using resampling techniques (SMOTE), but small event counts inherently limit model stability. The timing of predictor availability is uncertain because the registry lacks specific data-entry timestamps, complicating early prognostication in real clinical workflows. Multicenter data collection can introduce heterogeneity in coding standards and patient management protocols, though it improves generalizability compared with single-center designs. Finally, residual confounding by unmeasured variables, such as nutritional status, mobility status, or comprehensive wound-care data, likely remains.

5. Conclusions

Our findings suggest that ML offers a valuable framework for predicting short-term mortality in TSCI—key factors such as ventilator use and ASIA A classification echo well-established clinical predictors. PU prediction remained challenging, suggesting that enhanced model performance may depend on larger datasets and the incorporation of richer variables, especially those reflecting mobility and wound care factors. By focusing on interpretability alongside model performance, this study provides insights into both the feasibility and the practical considerations of deploying ML-based risk stratification in TSCI care.

6. Declarations

6.1. *Acknowledgments*

None.

6.2. *Conflict of interests*

The Authors declare no conflict of interest.

6.3. *Funding and supports*

This work was supported by Tehran University of Medical Sciences (TUMS), Tehran, Iran. The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

6.4. *Authors' contributions*

All authors fulfilled the four ICMJE authorship criteria, including substantial contributions to the conception or design of the work or the acquisition, analysis, or interpretation of data; drafting the work or revising it critically for important intellectual content; final approval of the version to be published; and agreement to be accountable for all aspects of the work.

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6.5. *Ethical statement*

This study was approved by the Institutional Review Board of Tehran University of Medical Sciences (IR.TUMS.SINAHOSPITAL.REC.1404.048).

6.6. *Informed consent*

All patients provided written informed consent for their anonymized clinical data to be included in the registry and used for research purposes in accordance with institutional and national ethical standards.

6.7. *Availability of supporting data*

Data used in this study is accessible through the corresponding author upon reasonable request.

6.8. *Using artificial intelligence chatbots statement*

The authors used artificial intelligence chatbot tools solely for language refinement and editorial assistance. No artificial intelligence tool was used to generate scientific content, analyse data, interpret results, or draw conclusions. The authors critically reviewed all assisted text and remain fully responsible for the final manuscript.

6.9. *Other declarations*

Protocol None was prepared for this study.

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Table 1: Prevalence of different variables in mortality and pressure ulcer subgroups

Variables	Total (n= 499)	Survival		FDR	Pressure ulcer		FDR
		Yes (n= 415)	No (n= 84)		Yes (n= 426)	No (n= 73)	
Age (year)							
Mean (95%)	38.54 (37.14, 39.95)	37.09 (35.61, 38.56)	45.73 (41.92, 49.54)	<0.001	38.82 (37.32, 40.32)	36.94 (32.90, 40.98)	0.531
Sex (%)							
Female	19.24 (15.78, 22.70)	19.28 (15.48, 23.07)	19.05 (10.65, 27.44)	1.000	18.08 (14.42, 21.73)	26.03 (15.96, 36.09)	0.268
Male	80.76 (77.30, 84.22)	80.72 (76.93, 84.52)	80.95 (72.56, 89.35)	1.000	81.92 (78.27, 85.58)	73.97 (63.91, 84.04)	0.268
Education Level (%)							
Illiterate	17.14 (13.81, 20.48)	14.88 (11.43, 18.32)	28.75 (18.83, 38.67)	<0.001	16.51 (12.95, 20.07)	20.83 (11.45, 30.21)	0.365
Primary school	19.39 (15.89, 22.89)	17.80 (14.10, 21.51)	27.50 (17.72, 37.28)	<0.001	19.38 (15.59, 23.17)	19.44 (10.30, 28.59)	0.365
Middle/high school	50.00 (45.57, 54.43)	51.71 (46.87, 56.54)	41.25 (30.46, 52.04)	<0.001	49.76 (44.97, 54.55)	51.39 (39.84, 62.93)	0.365
Higher education	13.47 (10.45, 16.49)	15.61 (12.10, 19.12)	2.50 (0.00, 5.92)	<0.001	14.35 (10.99, 17.72)	8.33 (1.95, 14.72)	0.365
Marital status (%)							
Married	65.33 (61.15, 69.51)	64.10 (59.48, 68.71)	71.43 (61.77, 81.09)	<0.001	66.90 (62.43, 71.37)	56.16 (44.78, 67.55)	0.432
Single	30.66 (26.62, 34.71)	33.49 (28.95, 38.03)	16.67 (8.70, 24.64)	<0.001	29.11 (24.79, 33.42)	39.73 (28.50, 50.95)	0.432
Divorced/widowed	3.21 (1.66, 4.75)	2.17 (0.77, 3.57)	8.33 (2.42, 14.24)	<0.001	3.05 (1.42, 4.68)	4.11 (0.00, 8.66)	0.432
Unknown	0.80 (0.02, 1.58)	0.24 (0.00, 0.71)	3.57 (0.00, 7.54)	<0.001	0.94 (0.02, 1.85)	0.00 (0.00, 0.00)	0.432
Nationality (%)							
Iranian	94.99 (93.08, 96.90)	96.14 (94.29, 98.00)	89.29 (82.67, 95.90)	0.045	95.31 (93.30, 97.31)	93.15 (87.36, 98.95)	0.652
Not Iranian	5.01 (3.10, 6.92)	3.86 (2.00, 5.71)	10.71 (4.10, 17.33)	0.045	4.69 (2.69, 6.70)	6.85 (1.05, 12.64)	0.652
Smoking status (%)							
Non-smoker	70.74 (66.75, 74.73)	72.05 (67.73, 76.37)	64.29 (54.04, 74.53)	0.313	70.42 (66.09, 74.76)	72.60 (62.37, 82.83)	0.823
Smoker	29.26 (25.27, 33.25)	27.95 (23.63, 32.27)	35.71 (25.47, 45.96)	0.313	29.58 (25.24, 33.91)	27.40 (17.17, 37.63)	0.823
Vital sign							
SBP(mmHg)	113.29 (111.76, 114.83)	113.91 (112.38, 115.45)	110.08 (104.86, 115.30)	0.142	113.69 (112.00, 115.38)	111.19 (107.48, 114.90)	0.434
DBP (mmHg)	71.13 (70.08, 72.18)	71.39 (70.34, 72.43)	69.83 (66.21, 73.45)	0.413	71.34 (70.25, 72.44)	70.01 (66.78, 73.25)	0.508
Pulse Rate (/minutes)	83.00 (81.80, 84.19)	83.08 (81.94, 84.21)	82.57 (78.04, 87.10)	0.848	82.72 (81.46, 83.98)	84.45 (80.95, 87.95)	0.447
SatO2 (%)	95.49 (95.17, 95.80)	95.76 (95.48, 96.05)	94.14 (92.97, 95.31)	<0.001	95.61 (95.27, 95.96)	94.80 (94.01, 95.59)	0.167
Respiratory Rate (/minutes)	17.97 (17.69, 18.25)	17.88 (17.59, 18.17)	18.39 (17.56, 19.22)	0.285	18.11 (17.79, 18.43)	17.33 (16.78, 17.89)	0.117
GCS (mean)	14.34 (14.13, 14.55)	14.53 (14.34, 14.72)	13.34 (12.51, 14.17)	<0.001	14.53 (14.35, 14.71)	13.29 (12.38, 14.21)	0.078
ASIA Impairment Scale (%)							
A	52.98 (48.47, 57.49)	46.21 (41.30, 51.12)	89.19 (82.11, 96.26)	<0.001	50.25 (45.35, 55.15)	68.57 (57.70, 79.45)	0.167
B	2.77 (1.28, 4.25)	3.03 (1.34, 4.72)	1.35 (0.00, 3.98)	<0.001	2.75 (1.15, 4.35)	2.86 (0.00, 6.76)	0.167
C	18.94 (15.39, 22.48)	21.72 (17.66, 25.78)	4.05 (0.00, 8.55)	<0.001	20.00 (16.08, 23.92)	12.86 (5.02, 20.70)	0.167
D	23.62 (19.78, 27.46)	27.02 (22.65, 31.39)	5.41 (0.25, 10.56)	<0.001	25.00 (20.76, 29.24)	15.71 (7.19, 24.24)	0.167
E	1.70 (0.53, 2.87)	2.02 (0.63, 3.41)	0.00 (0.00, 0.00)	<0.001	2.00 (0.63, 3.37)	0.00 (0.00, 0.00)	0.167
ASIA (mean)							
Motor score	45.51 (43.02, 48.00)	49.87 (47.25, 52.49)	23.19 (18.35, 28.03)	<0.001	47.18 (44.54, 49.83)	35.96 (29.12, 42.79)	0.018
Proprioception score	70.37 (67.24, 73.51)	76.86 (73.66, 80.06)	37.35 (31.19, 43.51)	<0.001	72.41 (69.07, 75.76)	58.61 (50.11, 67.12)	0.018
Superficial sensation score	70.02 (66.86, 73.18)	76.49 (73.25, 79.73)	37.09 (30.96, 43.22)	<0.001	72.06 (68.68, 75.44)	58.24 (49.79, 66.68)	0.018
Complete SCI (%)	54.31 (49.78, 58.84)	47.69 (42.74, 52.65)	89.19 (82.11, 96.26)	<0.001	51.78 (46.84, 56.71)	68.57 (57.70, 79.45)	0.060

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Variables	Total (n= 499)	Survival		FDR	Pressure ulcer		FDR
		Yes (n= 415)	No (n= 84)		Yes (n= 426)	No (n= 73)	
SCI Type (%)							
Paraparesis	16.94 (13.63, 20.24)	19.90 (16.05, 23.76)	2.38 (0.00, 5.64)	<0.001	17.73 (14.09, 21.37)	12.33 (4.79, 19.87)	0.070
Paraplegic	41.53 (37.20, 45.87)	42.96 (38.18, 47.74)	34.52 (24.36, 44.69)	<0.001	42.32 (37.61, 47.03)	36.99 (25.91, 48.06)	0.070
Hemiplegia/hemiparesis/not applicable	8.27 (5.84, 10.69)	8.98 (6.22, 11.74)	4.76 (0.21, 9.32)	<0.001	8.75 (6.05, 11.44)	5.48 (0.26, 10.70)	0.070
Quadriparesis	7.86 (5.49, 10.23)	8.74 (6.01, 11.46)	3.57 (0.00, 7.54)	<0.001	8.51 (5.85, 11.17)	4.11 (0.00, 8.66)	0.070
Quadriplegic	25.40 (21.57, 29.23)	19.42 (15.60, 23.24)	54.76 (44.12, 65.41)	<0.001	22.70 (18.70, 26.69)	41.10 (29.81, 52.38)	0.070
Pain score							
Mean (CI%)	5.85 (5.51, 6.19)	5.78 (5.42, 6.15)	6.35 (5.32, 7.38)	0.422	5.89 (5.49, 6.29)	5.68 (5.04, 6.32)	0.669
Number of injured vertebrae							
Mean (95%CI)	2.09 (1.96, 2.23)	2.04 (1.89, 2.19)	2.36 (2.08, 2.63)	0.158	1.99 (1.85, 2.13)	2.68 (2.31, 3.06)	0.005
Injuries (%)							
No injury	57.31 (52.97, 61.65)	59.76 (55.04, 64.48)	45.24 (34.59, 55.88)	0.045	58.92 (54.25, 63.59)	47.95 (36.49, 59.41)	0.243
Traumatic brain injury	11.62 (8.81, 14.44)	8.67 (5.97, 11.38)	26.19 (16.79, 35.59)	<0.001	11.50 (8.47, 14.53)	12.33 (4.79, 19.87)	1.000
Fracture/dislocation	27.66 (23.73, 31.58)	27.71 (23.40, 32.02)	27.38 (17.85, 36.92)	1.000	25.59 (21.44, 29.73)	39.73 (28.50, 50.95)	0.066
Internal bleeding	12.02 (9.17, 14.88)	10.60 (7.64, 13.56)	19.05 (10.65, 27.44)	0.103	11.27 (8.26, 14.27)	16.44 (7.94, 24.94)	0.455
C1-C2 injury	5.41 (3.43, 7.40)	5.06 (2.95, 7.17)	7.14 (1.64, 12.65)	0.736	5.16 (3.06, 7.27)	6.85 (1.05, 12.64)	0.823
Cervical injury	45.29 (40.92, 49.66)	38.55 (33.87, 43.24)	78.57 (69.80, 87.35)	<0.001	43.66 (38.95, 48.37)	54.79 (43.38, 66.21)	0.243
Thoracic injury	35.07 (30.88, 39.26)	37.59 (32.93, 42.25)	22.62 (13.67, 31.57)	0.031	35.45 (30.90, 39.99)	32.88 (22.10, 43.65)	0.823
Lumbar injury	30.46 (26.42, 34.50)	33.73 (29.19, 38.28)	14.29 (6.80, 21.77)	0.002	31.92 (27.50, 36.35)	21.92 (12.43, 31.41)	0.245
Sacral injury	2.40 (1.06, 3.75)	2.41 (0.93, 3.89)	2.38 (0.00, 5.64)	1.000	2.11 (0.75, 3.48)	4.11 (0.00, 8.66)	0.574
First aid given							
Yes	18.84 (15.14, 22.53)	16.11 (12.31, 19.91)	32.86 (21.85, 43.86)	0.005	14.36 (10.75, 17.98)	42.65 (30.89, 54.40)	<0.001
Immobilization (%)							
Neck	39.88 (35.58, 44.18)	38.80 (34.11, 43.48)	45.24 (34.59, 55.88)	0.450	39.20 (34.57, 43.84)	43.84 (32.45, 55.22)	0.646
Spine	46.29 (41.92, 50.67)	45.54 (40.75, 50.33)	50.00 (39.31, 60.69)	0.670	47.18 (42.44, 51.92)	41.10 (29.81, 52.38)	0.556
Limb	22.65 (18.97, 26.32)	22.17 (18.17, 26.17)	25.00 (15.74, 34.26)	0.769	23.94 (19.89, 28.00)	15.07 (6.86, 23.27)	0.248
No	2.20 (0.92, 3.49)	2.65 (1.11, 4.20)	0.00 (0.00, 0.00)	0.410	1.64 (0.44, 2.85)	5.48 (0.26, 10.70)	0.243
Ventilator use (%)							
Yes	22.65 (18.97, 26.32)	11.57 (8.49, 14.64)	77.38 (68.43, 86.33)	<0.001	18.78 (15.07, 22.49)	45.21 (33.79, 56.62)	<0.001
Urinary or fecal incontinence (%)							
Yes	35.07 (30.88, 39.26)	38.80 (34.11, 43.48)	16.67 (8.70, 24.64)	<0.001	37.56 (32.96, 42.16)	20.55 (11.28, 29.82)	0.037
Presence of other pain (%)							
No	59.92 (55.62, 64.22)	60.00 (55.29, 64.71)	59.52 (49.03, 70.02)	<0.001	62.91 (58.32, 67.50)	42.47 (31.13, 53.80)	0.023
Yes	35.27 (31.08, 39.46)	37.59 (32.93, 42.25)	23.81 (14.70, 32.92)	<0.001	32.39 (27.95, 36.84)	52.05 (40.59, 63.51)	0.023
Unable to assess	4.81 (2.93, 6.69)	2.41 (0.93, 3.89)	16.67 (8.70, 24.64)		4.69 (2.69, 6.70)	5.48 (0.26, 10.70)	
Injury cause (%)							
Traffic accident	52.10 (47.72, 56.49)	52.53 (47.73, 57.33)	50.00 (39.31, 60.69)	0.769	50.94 (46.19, 55.69)	58.90 (47.62, 70.19)	0.432
Fall	40.28 (35.98, 44.58)	39.52 (34.81, 44.22)	44.05 (33.43, 54.66)	0.769	41.78 (37.10, 46.47)	31.51 (20.85, 42.16)	0.432
Other	7.62 (5.29, 9.94)	7.95 (5.35, 10.55)	5.95 (0.89, 11.01)	0.769	7.28 (4.81, 9.74)	9.59 (2.83, 16.34)	0.432
Injury situation (%)							

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Variables	Total (n= 499)	Survival		FDR	Pressure ulcer		FDR
		Yes (n= 415)	No (n= 84)		Yes (n= 426)	No (n= 73)	
Car passenger	63.08 (57.21, 68.94)	62.39 (55.95, 68.82)	66.67 (52.41, 80.92)	0.727	65.44 (59.11, 71.77)	51.16 (36.22, 66.10)	0.094
Motorcyclist	16.92 (12.37, 21.48)	16.51 (11.58, 21.44)	19.05 (7.17, 30.92)	0.727	17.51 (12.45, 22.57)	13.95 (3.60, 24.31)	0.094
Other	20.00 (15.14, 24.86)	21.10 (15.68, 26.52)	14.29 (3.70, 24.87)	0.727	17.05 (12.05, 22.05)	34.88 (20.64, 49.13)	0.094
Type of activity during injury (%)							
Work-related	38.68 (34.40, 42.95)	37.83 (33.17, 42.50)	42.86 (32.27, 53.44)	0.207	41.31 (36.64, 45.99)	23.29 (13.59, 32.98)	0.023
Recreational	18.64 (15.22, 22.05)	19.04 (15.26, 22.81)	16.67 (8.70, 24.64)	0.207	16.43 (12.91, 19.95)	31.51 (20.85, 42.16)	0.023
Sports/unspecified	5.01 (3.10, 6.92)	4.10 (2.19, 6.00)	9.52 (3.25, 15.80)	0.207	4.93 (2.87, 6.99)	5.48 (0.26, 10.70)	0.023
Other	37.68 (33.42, 41.93)	39.04 (34.34, 43.73)	30.95 (21.07, 40.84)	0.207	37.32 (32.73, 41.92)	39.73 (28.50, 50.95)	0.023
Accident type (%)							
Collision	49.62 (43.54, 55.69)	48.17 (41.53, 54.80)	57.14 (42.18, 72.11)	0.493	47.93 (41.28, 54.57)	58.14 (43.39, 72.88)	0.445
Rollover	50.38 (44.31, 56.46)	51.83 (45.20, 58.47)	42.86 (27.89, 57.82)	0.493	52.07 (45.43, 58.72)	41.86 (27.12, 56.61)	0.445
Location of injury if non-accident (%)							
Household premises	14.23 (11.16, 17.29)	14.22 (10.86, 17.58)	14.29 (6.80, 21.77)	1.000	14.08 (10.78, 17.39)	15.07 (6.86, 23.27)	0.574
Industrial or construction sites	12.22 (9.35, 15.10)	12.05 (8.92, 15.18)	13.10 (5.88, 20.31)	1.000	13.15 (9.94, 16.35)	6.85 (1.05, 12.64)	0.574
Agricultural area	10.02 (7.39, 12.65)	10.12 (7.22, 13.02)	9.52 (3.25, 15.80)	1.000	10.56 (7.64, 13.48)	6.85 (1.05, 12.64)	0.574
Other	11.62 (8.81, 14.44)	11.33 (8.28, 14.37)	13.10 (5.88, 20.31)	1.000	11.50 (8.47, 14.53)	12.33 (4.79, 19.87)	0.574
Missing	51.90 (47.52, 56.29)	52.29 (47.48, 57.09)	50.00 (39.31, 60.69)	1.000	50.70 (45.96, 55.45)	58.90 (47.62, 70.19)	0.574
Height of fall (m) (%)							
Yes	4.59 (3.98, 5.21)	4.80 (4.10, 5.49)	3.70 (2.47, 4.94)	0.646	4.52 (3.89, 5.15)	5.15 (2.84, 7.47)	0.285
Injury protection if non-pedestrian (%)							
Helmet	54.11 (49.74, 58.48)	53.01 (48.21, 57.81)	59.52 (49.03, 70.02)	0.578	54.23 (49.49, 58.96)	53.42 (41.98, 64.87)	0.646
Missing	33.27 (29.13, 37.40)	34.46 (29.89, 39.03)	27.38 (17.85, 36.92)	0.578	33.80 (29.31, 38.29)	30.14 (19.61, 40.66)	0.646
Seatbelt	12.63 (9.71, 15.54)	12.53 (9.34, 15.72)	13.10 (5.88, 20.31)	0.578	11.97 (8.89, 15.05)	16.44 (7.94, 24.94)	0.646
Type of transfer (%)							
Ambulance	86.67 (83.67, 89.66)	86.65 (83.37, 89.93)	86.75 (79.45, 94.04)	1.000	87.20 (84.02, 90.39)	83.56 (75.06, 92.06)	0.574
Non-ambulance	13.33 (10.34, 16.33)	13.35 (10.07, 16.63)	13.25 (5.96, 20.55)	1.000	12.80 (9.61, 15.98)	16.44 (7.94, 24.94)	0.574
Triage to admission interval (%)							
Under 12 hours	72.14 (68.21, 76.08)	73.49 (69.25, 77.74)	65.48 (55.31, 75.64)	0.279	71.60 (67.31, 75.88)	75.34 (65.46, 85.23)	0.823
More than 12 hours	17.84 (14.48, 21.19)	17.59 (13.93, 21.25)	19.05 (10.65, 27.44)	0.279	18.08 (14.42, 21.73)	16.44 (7.94, 24.94)	0.823
Missing	10.02 (7.39, 12.65)	8.92 (6.17, 11.66)	15.48 (7.74, 23.21)	0.279	10.33 (7.44, 13.22)	8.22 (1.92, 14.52)	0.823
Injury to admission interval (%)							
Under 12 hours	49.70 (45.31, 54.09)	49.64 (44.83, 54.45)	50.00 (39.31, 60.69)	0.142	51.41 (46.66, 56.15)	39.73 (28.50, 50.95)	0.305
More than 12 hours	43.49 (39.14, 47.84)	42.41 (37.65, 47.16)	48.81 (38.12, 59.50)	0.142	41.78 (37.10, 46.47)	53.42 (41.98, 64.87)	0.305
Missing	6.81 (4.60, 9.02)	7.95 (5.35, 10.55)	1.19 (0.00, 3.51)	0.142	6.81 (4.42, 9.20)	6.85 (1.05, 12.64)	0.305
More than 5 missing values (%)							
Yes	20.04 (16.53, 23.55)	19.04 (15.26, 22.81)	25.00 (15.74, 34.26)	0.410	22.07 (18.13, 26.00)	8.22 (1.92, 14.52)	0.060

Values are either percentages or means with 95% confidence intervals (CIs). Statistical tests include the t-test, the Mann–Whitney U test, and the chi-square test, as appropriate. FDR: false discovery rate; PU: pressure ulcer; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure; SatO2:O2 saturation; GCS: Glasgow Coma Scale; SCI: Spinal Cord Injury.

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Table 2: Evaluation of different models used for prediction of mortality

Classifier	Feature Selector	N	AUC	Specificity	Sensitivity	Balanced Accuracy	F1-score	Precision	Accuracy	Test-Train AUC
LGBMClassifier	LogisticRegression	18	0.85 (0.73, 0.94)	0.94 (0.88, 0.99)	0.47 (0.23, 0.71)	0.70 (0.58, 0.83)	0.52 (0.29, 0.73)	0.61 (0.33, 0.88)	0.86 (0.79, 0.92)	-0.06
KNeighborsClassifier	LogisticRegression	4	0.85 (0.77, 0.92)	0.92 (0.85, 0.97)	0.41 (0.18, 0.67)	0.66 (0.54, 0.79)	0.44 (0.21, 0.65)	0.50 (0.23, 0.77)	0.83 (0.75, 0.90)	-0.01
GaussianNB	RandomForestClassifier	8	0.85 (0.76, 0.92)	0.81 (0.72, 0.89)	0.71 (0.47, 0.92)	0.76 (0.63, 0.87)	0.53 (0.34, 0.70)	0.43 (0.25, 0.62)	0.79 (0.71, 0.87)	-0.06
LogisticRegression	LogisticRegression	18	0.85 (0.75, 0.93)	0.81 (0.72, 0.89)	0.70 (0.47, 0.92)	0.76 (0.63, 0.87)	0.53 (0.33, 0.70)	0.43 (0.25, 0.62)	0.79 (0.71, 0.87)	-0.07
MLPClassifier	RandomForestClassifier	4	0.84 (0.75, 0.93)	0.89 (0.82, 0.95)	0.53 (0.29, 0.78)	0.71 (0.58, 0.84)	0.51 (0.29, 0.70)	0.50 (0.27, 0.74)	0.83 (0.75, 0.90)	-0.08
XGBClassifier	LogisticRegression	8	0.84 (0.74, 0.93)	0.84 (0.76, 0.92)	0.53 (0.29, 0.77)	0.69 (0.56, 0.82)	0.45 (0.25, 0.64)	0.41 (0.21, 0.62)	0.79 (0.71, 0.87)	-0.06
RandomForestClassifier	LogisticRegression	10	0.83 (0.71, 0.93)	0.92 (0.85, 0.97)	0.47 (0.23, 0.71)	0.69 (0.57, 0.82)	0.49 (0.26, 0.70)	0.53 (0.27, 0.80)	0.84 (0.77, 0.91)	-0.08
SVC	RandomForestClassifier	8	0.83 (0.72, 0.92)	1.00 (1.00, 1.00)	0.00 (0.00, 0.00)	0.50 (0.50, 0.50)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.83 (0.75, 0.90)	-0.08
DecisionTreeClassifier	RandomForestClassifier	4	0.78 (0.63, 0.90)	0.88 (0.81, 0.95)	0.65 (0.40, 0.88)	0.76 (0.64, 0.88)	0.57 (0.37, 0.75)	0.52 (0.31, 0.75)	0.84 (0.76, 0.91)	-0.08

N: Number of Features Used; Model performance in mortality prediction. The 95% confidence intervals are calculated by bootstrapping. AUC: area under the receiver operating characteristic curve.

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Table 3: Evaluation of different models used for prediction of pressure ulcer

Classifier	Feature Selector	N	AUC	Specificity	Sensitivity	Balanced Accuracy	F1-score	Precision	Accuracy	Test- Train AUC
RandomForestClassifier	RandomForestClassifier	36	0.83 (0.72, 0.93)	0.89 (0.82, 0.95)	0.65 (0.40, 0.87)	0.77 (0.64, 0.89)	0.59 (0.38, 0.76)	0.55 (0.33, 0.77)	0.85 (0.78, 0.92)	0.15
XGBClassifier	LogisticRegression	8	0.81 (0.71, 0.90)	0.96 (0.92, 1.00)	0.00 (0.00, 0.00)	0.48 (0.46, 0.50)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.80 (0.72, 0.88)	0.16
LGBMClassifier	RandomForestClassifier	24	0.80 (0.66, 0.91)	0.94 (0.88, 0.99)	0.35 (0.13, 0.59)	0.65 (0.53, 0.77)	0.42 (0.17, 0.64)	0.55 (0.23, 0.86)	0.84 (0.77, 0.91)	0.19
LogisticRegression	RandomForestClassifier	42	0.79 (0.69, 0.88)	0.94 (0.88, 0.99)	0.24 (0.05, 0.45)	0.59 (0.49, 0.70)	0.30 (0.08, 0.53)	0.45 (0.11, 0.80)	0.82 (0.74, 0.89)	0.11
GaussianNB	RandomForestClassifier	22	0.79 (0.68, 0.88)	0.84 (0.76, 0.92)	0.41 (0.18, 0.67)	0.63 (0.50, 0.75)	0.37 (0.17, 0.57)	0.35 (0.14, 0.57)	0.77 (0.68, 0.85)	0.14
KNeighborsClassifier	LogisticRegression	6	0.64 (0.47, 0.80)	0.89 (0.82, 0.95)	0.41 (0.18, 0.65)	0.65 (0.53, 0.78)	0.42 (0.19, 0.62)	0.44 (0.20, 0.69)	0.81 (0.73, 0.88)	0.01
MLPClassifier	RandomForestClassifier	14	0.59 (0.43, 0.76)	0.78 (0.69, 0.87)	0.35 (0.13, 0.60)	0.57 (0.44, 0.70)	0.29 (0.11, 0.47)	0.25 (0.08, 0.43)	0.71 (0.62, 0.80)	-0.09
DecisionTreeClassifier	LogisticRegression	8	0.58 (0.43, 0.72)	0.82 (0.73, 0.90)	0.18 (0.00, 0.38)	0.50 (0.40, 0.61)	0.17 (0.00, 0.34)	0.17 (0.00, 0.36)	0.71 (0.62, 0.80)	-0.09

N: Number of Features Used; Model performance in PU prediction. The 95% confidence intervals are calculated by bootstrapping. AUC: Area under the receiver operating characteristic curve.

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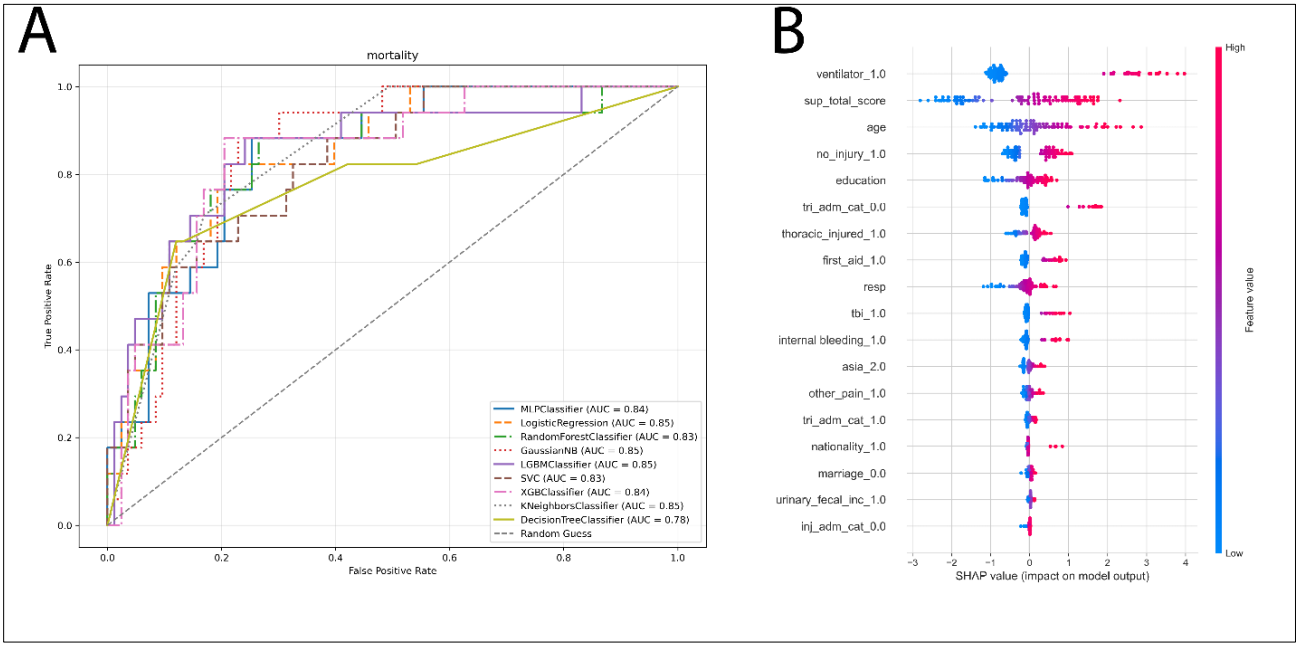

Figure 1: A: Performance of different machine learning models in predicting in-hospital mortality; B: Shapley Additive Explanations (SHAP) analysis of features in the Light-GBM model for predicting in-hospital mortality. AUC: area under the receiver operating characteristic curve.

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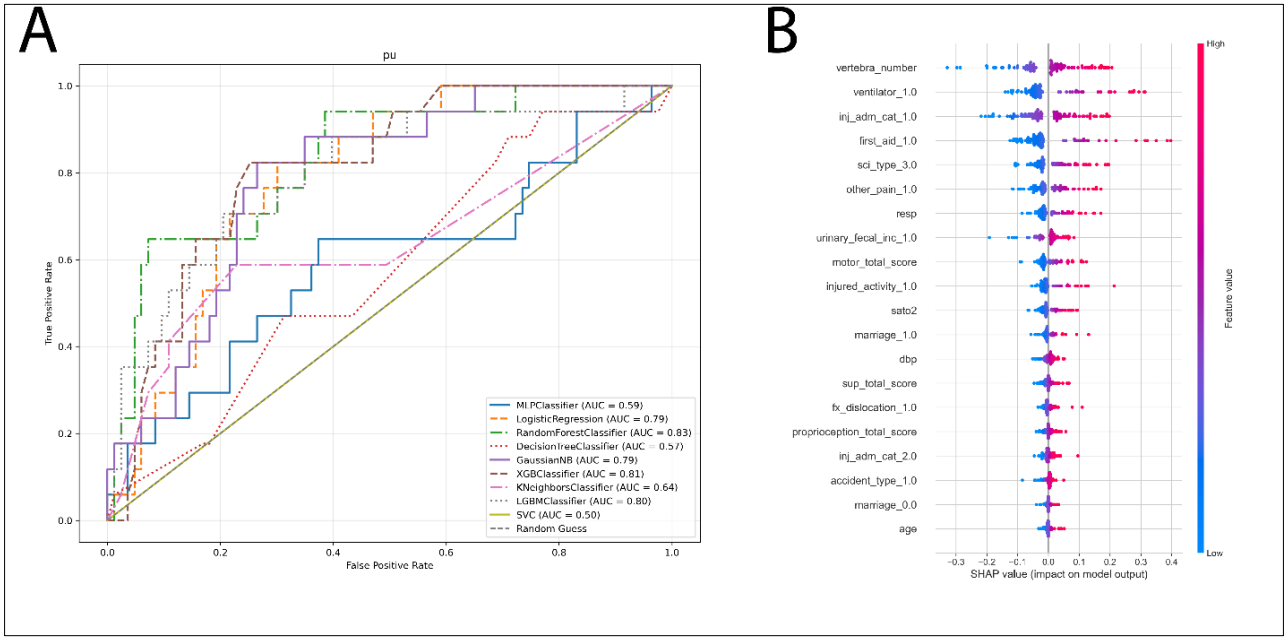

Figure 2: A: Performance of different machine learning models in predicting pressure ulcer; B: Shapley Additive Explanations (SHAP) analysis of features in the Random Forest model for predicting pressure ulcer. AUC: area under the receiver operating characteristic curve.

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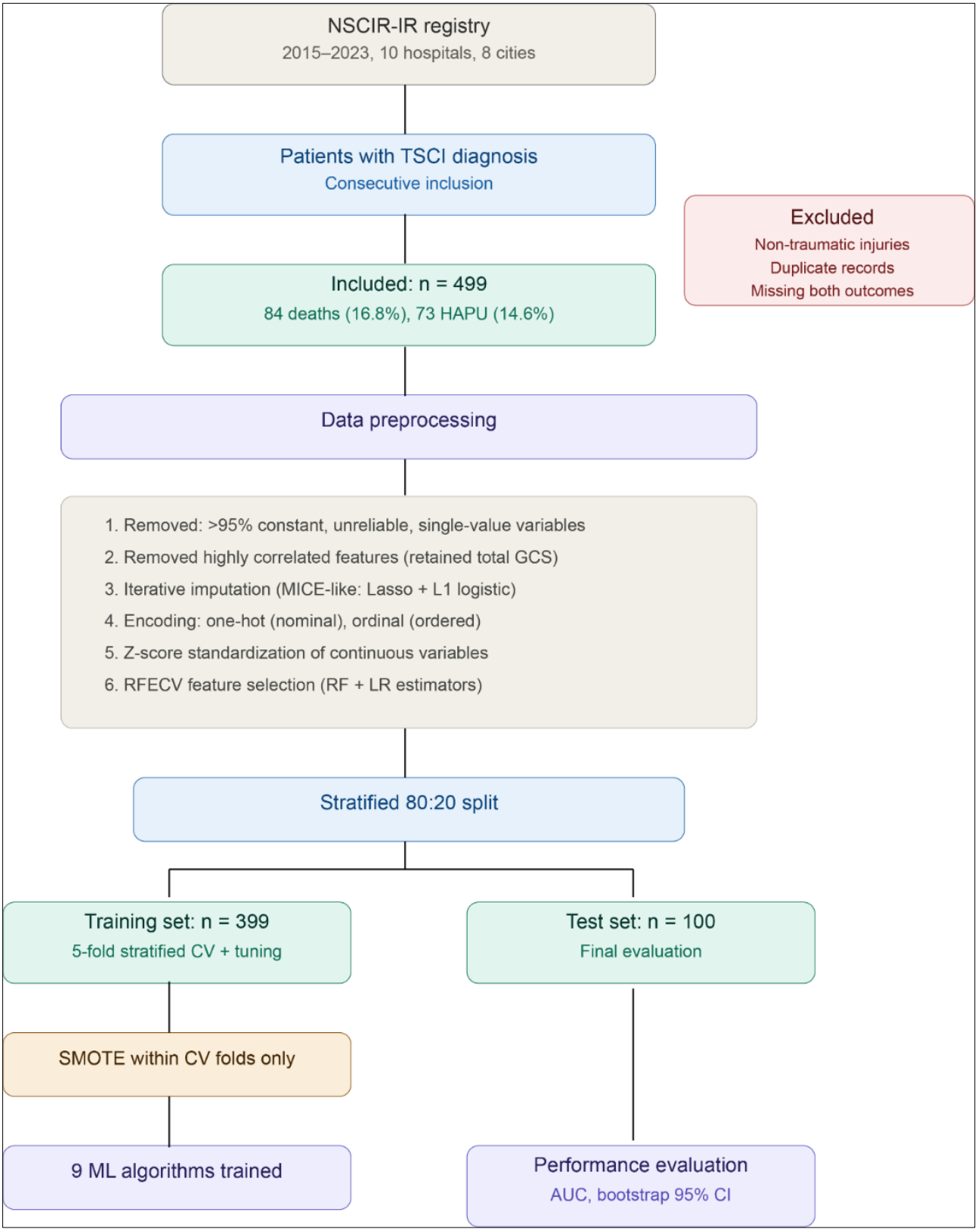

Supplementary Figure 1: Study flowchart. TSCI: traumatic spinal cord injury, NSCIR-IR: National Spinal Cord Injury Registry of Iran, MICE: multiple imputation by chained equations, RFECV: recursive feature elimination with cross-validation, CV: cross-validation, ML: machine learning, SMOTE: synthetic minority oversampling technique, AUC: area under the receiver operating characteristic curve, CI: confidence interval, RF: random forest, LR: logistic regression, GCS: Glasgow Coma Scale.

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