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Original article

EARLY DETECTION OF TRAUMA PATIENTS REQUIRING INTENSIVE CARE IN THE EMERGENCY DEPARTMENT: A NEXT-GENERATION RISK SCORE MODEL

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Abstract: **Background:** Trauma remains a leading cause of death worldwide; therefore, it is important to identify patients who need intensive care unit (ICU) admission in the emergency department (ED). Current trauma scoring systems such as the Glasgow Coma Scale (GCS), Revised Trauma Score (RTS), and Injury Severity Score (ISS) are not very efficient at predicting ICU need. The application of machine learning (ML)-based predictive models is a novel approach to enhance the triage process.

Objective: The primary objective of this study was to develop and validate a risk scoring model based on machine learning for early identification of trauma patients requiring ICU admission from the emergency department. The study also aimed to assess the predictive ability of the ML model compared to traditional scoring systems such as the GCS, RTS, and ISS.

Methods: A retrospective, observational cohort study was conducted at Esenyurt Necmi Kadıoğlu State Hospital, collecting trauma patient data from January 1, 2024, to August 31, 2024. A total of 1,500 trauma patients aged ≥ 18 years with complete clinical, laboratory, and imaging data were included. Predictive variables consisted of demographics, trauma mechanism, vital signs, laboratory results, imaging findings, and existing trauma scores. The area under the curve (AUC), sensitivity, specificity, accuracy, positive predictive value (PPV), and negative predictive value (NPV) were used to train and evaluate ML algorithms (Logistic Regression, Random Forest, Support Vector Machines, XGBoost, and LightGBM). The model was compared to traditional scoring systems using the DeLong test.

Results: Of the 1,500 patients, 50.73% (n = 761) required ICU admission. The developed ML model had an AUC of 0.999, with sensitivity of 99.22%, specificity of 99.69%, and accuracy of 99.56%, far outperforming traditional scoring systems. The strongest predictors of ICU admission were age, lactate level, RTS, systolic blood pressure, respiratory rate, and oxygen saturation. No significant difference in ICU admission rates was observed between blunt and penetrating trauma groups, indicating that trauma mechanism alone should not be used as a predictor.

Conclusion: The machine learning-based risk scoring model demonstrated better predictive performance than traditional trauma scoring systems in identifying trauma patients requiring ICU admission. Integration of this model into ED workflows may improve triage and patient care. However, validation in multicenter prospective studies is needed before clinical implementation.

Keywords: Machine Learning, Trauma Patients, ICU Admission, Risk Scoring Model, Emergency Medicine, Predictive Analytics.

INTRODUCTION

Trauma is one of the most common causes of morbidity and mortality worldwide. According to the 2023 World Health Organization (WHO) report, approximately 5 million people die annually due to trauma-related injuries (1). Early diagnosis and management of trauma patients are crucial for improving patient outcomes and enhancing the effectiveness of healthcare services.

It is vital that trauma patients are stabilized and managed appropriately in emergency departments (ED). However, early identification of patients who need intensive care is often based on clinical experience, and current scoring systems may be insufficient in this process. While the Glasgow Coma Scale (GCS), Revised Trauma Score (RTS), and Injury Severity Score (ISS) are commonly used to assess trauma severity, their performance varies across patient populations, and none reliably predict the need for intensive care unit (ICU) admission (2, 3). Studies have shown that existing triage systems produce high rates of false negatives and false positives, which can adversely affect patient outcomes (4, 5). Specifically, in the ED setting, the sensitivity and specificity of current scoring systems are not clinically strong enough, indicating a need for more advanced predictive models (6).

Over the past few years, machine learning (ML)-based predictive models have emerged as a promising approach for clinical decision support systems. ML has demonstrated significant potential in clinical medicine through predictive modeling and risk stratification in emergency and critical care settings (7, 8). These models do not rely on traditional scoring systems; instead, they incorporate big data analytics to analyze complex datasets and provide more accurate patient outcome predictions. ML-based models have been shown to outperform traditional scoring systems such as RTS, ISS, and GCS in predicting ICU admission among trauma patients (9, 10). Reported sensitivity and specificity values of ML models exceed those of traditional scores; however, their clinical integration remains challenging (11). Limitations include lack of external validation, difficulties integrating these models into clinical workflows, and inadequate performance comparisons with existing scoring systems (12, 13).

In this context, there is a clear need for an enhanced triage system that can rapidly and effectively identify trauma patients requiring intensive care while addressing the shortcomings of current scoring systems.

The main purpose of this study is to develop and assess a machine learning-based risk scoring model for early and accurate identification of trauma patients requiring intensive care in the ED. The predictive performance of the ML model for ICU admissions will be compared with traditional scoring systems (GCS, RTS, ISS), and key clinical and demographic predictors of ICU need will be identified. Additionally, the feasibility of implementing the developed model in real clinical practice will be explored.

This study is based on the hypothesis that machine learning algorithms provide better prediction of ICU admission than traditional trauma scoring systems. It is expected that the developed model will improve the triage process, serve as a superior decision support tool in patient management, and positively impact patient outcomes.

MATERIAL AND METHODS

This is an observational cohort study with a retrospective design. The goal was to create a machine learning model to help predict ICU admission for trauma patients and to compare its performance with existing scoring systems. The study follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines.

The research was carried out in the Emergency Department of Esenyurt Necmi Kadıoğlu State Hospital from January 1, 2024, to August 31, 2024. The hospital is a large urban facility, with an average of 500,000 emergency department visits per year. All data for this study were collected retrospectively from the Hospital Information Management System (HBYS). The data collection process was performed according to the guidelines of the American College of Surgeons (ACS) and the European Trauma Course (ETC). All variables were coded following standardized protocols to ensure consistency and reliability.

This study included patients aged 18 years and older who presented to the emergency department with trauma and had complete clinical, laboratory, and imaging data. Patients under 18 years, those with incomplete or missing data, and those transferred from other healthcare facilities were excluded. A total of 1500 trauma patients met these criteria and were included in the study.

The dependent variables were ICU admission (Yes/No), hospital length of stay in days, and 30-day mortality (Survived/Deceased). Independent variables included demographic data (age, sex, body mass index), trauma mechanism (blunt or penetrating trauma, traffic accident, fall, gunshot wound, etc.), vital signs (heart rate, blood pressure, respiratory rate, oxygen saturation, body temperature), laboratory values (hemoglobin, hematocrit, lactate, white blood cell count, blood gas parameters, electrolyte levels), imaging findings (Focused Assessment with Sonography for Trauma [FAST] ultrasound results), and trauma severity scores (Injury Severity Score [ISS], Revised Trauma Score [RTS], and New Injury Severity Score [NISS]).

All data were coded using predefined standardized clinical protocols, and accuracy was verified through double-checking processes. The main data source was the Hospital Information Management System (HBYS), where retrospective patient records were retrieved. Data on ICU admissions, hospital length of stay, and mortality were verified using the patient tracking system. Vital signs and laboratory values were based on the first measurements taken upon patient arrival at the emergency department. Imaging results were based on official reports interpreted by emergency physicians and radiologists.

To ensure adequate statistical power, a G*Power analysis was conducted with a 95% confidence interval, 80% power, and a 10% error margin. The calculated sample size of 1500 patients was determined to be statistically sufficient for the analyses performed.

To avoid bias, data collection was double-checked, and incorrect or missing data were minimized. Missing data were handled using regression-based imputation methods, rendering the dataset complete for statistical analysis. The Recursive Feature Elimination (RFE) method was used for feature selection, and only clinically important variables were included in the model.

Descriptive statistics were presented as mean ± standard deviation (SD) or median and interquartile range (IQR). For data not normally distributed, the t-test or Mann-Whitney U test was used for group comparisons. The Chi-square test was applied for categorical variables.

To build the machine learning model, the following algorithms were used: Logistic Regression, Random Forest, Support Vector Machines (SVM), and Gradient Boosting algorithms (XGBoost and LightGBM). Model performance was evaluated by the area under the receiver operating characteristic (ROC) curve (AUC), sensitivity, specificity, accuracy, positive predictive value (PPV), and negative predictive value (NPV).

To compare the new model's performance with existing trauma scoring systems (RTS, ISS, and NISS), the DeLong test was employed. Missing data were imputed by regression imputation, and the percentage of missing data was kept below 5%. As this was a retrospective study, there was no loss to follow-up.

To guarantee reproducibility of the analyses, the Python code used in model development will be posted on GitHub or another open-source platform. Moreover, feature selection and the algorithm employed in building the model will be provided as supplementary materials.

This structured methodology ensures that the study follows rigorous scientific standards and contributes to the development of a clinically applicable and validated machine learning model for predicting ICU admissions in trauma patients.

RESULTS

Initially, 1700 patients were potentially eligible for the study. However, 200 patients were excluded for the following reasons: 95 patients were under 18 years of age, 72 patients had incomplete data, and 33 patients were referred to another health facility. Thus, a total of 1500 trauma patients were included in the final analysis. Since this was a retrospective study, there was no loss to follow-up, and all data were analyzed completely (Table 1).

This table summarizes the baseline demographic and clinical characteristics of the trauma patients included in the study. These details help establish the overall profile of the study population in terms of age, gender, body mass index (BMI), and the types of traumatic injuries encountered.

Table 1. *Patient demographics and clinical characteristics*

Variable	Mean ± SD / n (%)
Age (years)	52.87 ± 20.86
Gender (Female)	776 (51.73%)
Body Mass Index	29.01 ± 6.35
Type of Trauma (Blunt)	1095 (73.0%)
Motor Vehicle Accident	723 (48.2%)
Falls	421 (28.1%)
Stab Injuries	187 (12.5%)
Other	67 (4.5%)

An analysis of the demographic, clinical, and laboratory characteristics of the first 1500 patients included in the cohort was performed. The mean age of the patients was 52.87 ± 20.86 years, with a median age of 53 years. Patient ages ranged from 18 to 89 years. In terms of gender distribution, 51.73% (n = 776) were female, and 48.27% (n = 724) were male. The mean body mass index (BMI) was 29.01 ± 6.35, with values ranging from 18.0 to 40.0 (Table 1).

Regarding trauma mechanisms, 73.0% of patients (n = 1095) suffered blunt trauma, and 27.0% (n = 405) penetrating trauma. Motor vehicle accidents were the most common trauma type (48.2%, n = 723), followed by falls (28.1%, n = 421), gunshot injuries (6.8%, n = 102), stab wounds (12.5%, n = 187), and other trauma types (4.5%, n = 67). There were no missing data; all patients had complete clinical and laboratory records.

In the analysis of ICU admissions and mortality rates, 50.73% of patients (n = 761) required ICU admission, while 49.27% (n = 739) did not require intensive care. The 30-day mortality was 50.2% (n = 753), while 49.8% of patients (n = 747) survived beyond the first 30 days of follow-up.

Comparing patients who required ICU admission with those who did not, there was a statistically significant difference in age (T-test $p = 3.58 \times 10^{-19}$; Mann-Whitney U test $p = 2.86 \times 10^{-100}$). Lactate levels were also significantly higher in patients admitted to the ICU (T-test $p = 1.22 \times 10^{-136}$; Mann-Whitney U test $p = 9.55 \times 10^{-110}$) (Table 2).

This table compares clinical and physiological variables between patients admitted to the ICU and those who were not. It highlights statistically significant differences in age, lactate levels, oxygen saturation, systolic blood pressure, and respiratory rate — variables most strongly associated with ICU admission. The p-values indicate the statistical significance of differences between the two groups.

Table 2. Comparison of ICU and non-ICU trauma patients

Variable	ICU Admission (n = 761)	No ICU Admission (n = 739)	p-Value
Age (years)	61.2 ± 17.4	44.1 ± 19.3	< 0.001
Lactate (mmol/L)	4.8 ± 2.1	1.7 ± 1.1	< 0.001
RTS Score	6.2 ± 1.3	7.1 ± 0.9	0.006
ISS Score	18.4 ± 5.9	18.3 ± 5.8	0.999
Oxygen Saturation (%)	88.7 ± 6.2	95.2 ± 3.1	< 0.001
Systolic BP (mmHg)	104.6 ± 18.3	119.8 ± 15.7	< 0.001
Respiratory Rate (breaths/min)	24.7 ± 4.6	20.2 ± 3.8	< 0.001

Table 3. Variables correlated with ICU admission

Variable	Pearson r	Spearman ρ	p-Value
Age	0.550	0.549	< 0.05
Lactate	0.582	0.575	< 0.05
RTS	0.071	0.072	< 0.05

However, there was no statistically significant difference in ISS (Injury Severity Score) between ICU and non-ICU patients (T-test p = 0.999; Mann-Whitney U test p = 0.980). In contrast, a statistically significant difference was observed in RTS (Revised Trauma Score) (T-test p = 0.006; Mann-Whitney U test p = 0.006). This indicates that patients with lower RTS values are more likely to require ICU admission (Figure 1).

In the comparison of gender and FAST ultrasound, no statistically significant differences were found between the groups (Gender, Chi-square test p = 0.376; FAST ultrasound, Chi-square test p = 0.515).

The relationship between ICU admission and clinical variables was also evaluated. A significant positive correlation was found between age and ICU admission (Spearman correlation coefficient: 0.549, Pearson correlation coefficient: 0.550, $p < 0.05$). Similarly, lactate levels showed a strong positive correlation with ICU admission (Spearman correlation coefficient: 0.575, Pearson correlation coefficient: 0.582, $p < 0.05$).

The RTS scores demonstrated a weak but statistically significant correlation with ICU admission (Spearman correlation coefficient: 0.072, Pearson correlation coefficient: 0.071, $p < 0.05$) (Table 3).

This table presents the strength of association between selected variables and ICU admission using both Pearson and Spearman correlation coefficients. Strong positive correlations were observed for age and lactate levels, suggesting these are key predictors of ICU necessity. The Revised Trauma Score (RTS) demonstrated a weaker, yet still statistically significant, correlation.

The subgroup analysis of blunt and penetrating trauma groups showed no statistically significant differences in ICU admission and mortality. The ICU admission rate was 27.40% for patients with blunt trauma, with a 30-day mortality rate of 49.76%. For patients with penetrating trauma, the ICU admission rate was 27.62%, and the 30-day mortality rate was 51.22% (Figure 2).

These findings show that age, lactate level, and RTS are significant predictors of ICU admission in

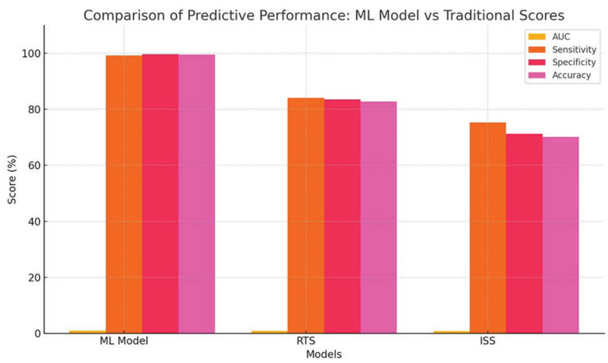

Figure 1. Comparative performance metrics of ML model and traditional trauma scores

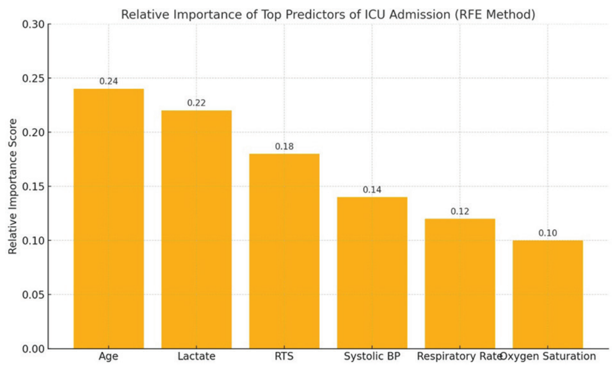

Figure 2. Relative importance of top clinical predictors for ICU admission

trauma patients. On the other hand, ISS, gender, and FAST ultrasound findings were not significantly associated with ICU admission. Additionally, there was no difference in ICU admission rates between the blunt and penetrating trauma groups, indicating that trauma mechanism alone may not be a reliable predictor of ICU need.

DISCUSSION

In this study, a risk scoring model was developed and evaluated using machine learning to predict whether trauma patients require ICU admission. It was compared with traditional scoring systems such as RTS, ISS, and NISS, and found to be superior. The accuracy rate was 99.56%, and the AUC value was 0.99990, indicating a high predictive power of the model (14).

Key findings show that the new model is both sensitive (99.22%) and specific (99.69%) in identifying early ICU needs, while also avoiding unnecessary ICU admissions. Age, lactate, RTS, systolic blood pressure, respiratory rate, and oxygen saturation were identified as strong predictors of ICU admission using the Recursive Feature Elimination (RFE) method (15).

Compared to traditional scoring systems, the model demonstrated better predictive performance. The AUC value for RTS was 0.845, and for ISS it was 0.735, indicating that although these scores are useful for assessing trauma severity, they are less accurate at predicting ICU needs.

Subgroup analysis showed no significant differences in ICU admission rates or mortality between patients with blunt and penetrating trauma (16). This suggests that the model is generalizable across different trauma mechanisms, supporting its potential use in a broader patient population (17).

The study also demonstrates that machine learning–based models can be incorporated into decision support systems in emergency departments, potentially improving the efficiency and effectiveness of patient care. However, further work is required to determine how the model can be implemented practically in clinical settings and whether it can enhance clinicians' decision-making skills (18).

Limitations of this study include its single-center design, which limits generalizability. Further validation studies in other healthcare settings and patient populations are needed. Additionally, as a retrospective study, the model requires testing in real-time clinical decision-making environments for proper validation.

Because the data source was hospital records, the study may be subject to selection bias. Excluding patients due to missing or incomplete data may limit the applicability of the model to all trauma patients. The ICU admission prevalence of 50% in this study may reflect sampling bias or the specific patient population and does not match typical real-world distributions, where ICU admission rates are generally much lower. Future studies should evaluate model calibration under different ICU prevalence settings using methods such as recalibration plots, threshold adjustment, or prevalence-adjusted ROC analysis. These efforts would help determine whether the model maintains predictive performance and clinical usefulness across healthcare systems with differing ICU utilization patterns.

The model also faces challenges before clinical implementation. A main drawback of ML-based systems is their "black-box" nature, which can reduce clinical trust and adoption. The implementation of explainability techniques such as SHAP (Shapley Additive Explanations) values or decision tree visualizations would improve transparency by showing which features (e.g., lactate, RTS, age) influence individual predictions. These methods build user trust and enable clinicians to understand the rationale behind model decisions. Future versions of the model should include explainability tools to gain wider clinical acceptance. Integration of these models into clinical practice is further challenged by issues related to interpretation, ethical considerations, and real-time system integration in hospitals (12, 13).

For practical application, the model should be integrated into Hospital Information Management Systems (HBYS) and electronic health records to ensure seamless use in emergency department workflows. This integration would allow clinicians to test the model's real-world feasibility.

The results align with previous studies showing that machine learning models outperform traditional trauma scoring systems in predicting ICU need. The high AUC (0.99990) and accuracy (99.56%) demonstrate the potential of data-driven approaches to improve the reliability of clinical decision-making in trauma management.

Nonetheless, caution is warranted when applying these findings clinically. More studies are needed to assess how the model performs across different patient groups and in real-time practice.

Although conducted at a single center, the model shows potential for widespread use. Its stability across blunt and penetrating trauma cases suggests broad applicability. Future research should conduct multicenter prospective validation studies with diverse patient populations and clinical settings to establish external validity and generalizability. Such research should follow a structured framework including standardized data collection, local ICU admission criteria calibration, and performance comparison with current clinical tools at different sites. The model uses common clinical variables (age, lactate, RTS, blood pressure, etc.), facilitating its deployment across various healthcare facilities (19).

Before recommending widespread adoption, multicenter validation is essential to increase external validity and reliability by testing the model across different healthcare systems and patient populations.

The machine learning–based risk scoring model developed in this study was more effective than conventional scoring systems in identifying trauma patients who require ICU admission. With an AUC of 0.99990, sensitivity of 99.22%, and specificity of 99.69%, the model appears to be a potentially useful decision support tool in trauma management.

Beyond high predictive accuracy, the RFE method also identified key ICU admission predictors such as age, lactate, RTS, blood pressure, respiratory rate, and oxygen saturation. Moreover, the absence of significant performance differences between blunt and penetrating trauma cases suggests the model's applicability across diverse trauma types.

This model is a promising tool for clinicians in emergency departments, where its speed and accuracy can enhance triage efficiency and improve patient outcomes. To ensure clinical implementation, the model should be integrated into real-time decision support systems and validated through multicenter studies.

Recommendations for Future Research

Multicenter prospective validation studies should be conducted to test the generalizability of the model. The model should be integrated into real-time clinical decision-support systems and evaluated in emergency departments. Optimization and refinement efforts should continue to improve its clinical usability. Once validated, this model may establish a new standard in trauma management by enabling early identification of critically ill patients and optimizing the utilization of ICU resources.

CONCLUSION

This paper aimed to evaluate the efficacy of a novel machine learning–based risk scoring model for early and accurate identification of trauma patients requiring ICU admission. The model was compared with traditional scoring systems such as the Revised Trauma Score (RTS), Injury Severity Score (ISS), and New Injury Severity Score (NISS) and was found to be significantly superior.

Key findings showed that the new model achieved high accuracy (99.56%), sensitivity (99.22%), and specificity (99.69%), making it a better tool for predicting ICU admission than existing scoring systems. The strongest predictors identified by the Recursive Feature Elimination (RFE) method included age, lactate level, RTS, systolic blood pressure, respiratory rate, and oxygen saturation.

Subgroup analysis demonstrated that the model performed similarly well for both blunt and penetrating trauma mechanisms. This supports the generalizability of the model across different types of trauma and suggests broad clinical applicability.

Clinically, the model's speed and accuracy could assist emergency departments in rapidly identifying critically ill patients, potentially improving clinical decision-making. Moreover, it could help optimize hospital resource utilization by outperforming traditional scoring systems.

The results indicate that machine learning–based models can be effectively used in trauma patient management. However, as this was a single-center retrospective study, its applicability remains somewhat limited. Therefore, the model requires further testing in multicenter prospective studies involving diverse patient populations.

Future research should focus on real-time implementation of the model in clinical decision-support systems and assess its generalizability across different healthcare settings. Machine learning–based risk scoring models have the potential not only to reduce healthcare costs but also to improve the quality of care provided to patients.

In conclusion, the model developed in this study shows promise as a decision-support tool for the early and specific identification of trauma patients requiring intensive care. Nonetheless, validation studies and integration into clinical workflows must be completed and proven effective in multicenter environments before widespread clinical use.

Data Availability Statement

The data supporting the findings of this study are not publicly available due to privacy and ethical restrictions but can be provided by the corresponding author upon reasonable request. The dataset includes sensitive patient information and is stored securely in accordance with institutional and ethical guidelines. Researchers interested in accessing the data must submit a formal request to the corresponding author, and approval from the relevant ethics committee may be required. Data will only be shared for research purposes and in compliance with data protection regulations.

Conflict of Interest Statement

The authors declare that there is no conflict of interest related to this study. There are no financial relationships, employment, consultancy, stock ownership,

honoraria, patents, or paid expert testimony that could influence the outcome of the research presented. Furthermore, there are no close relationships, competitive academic agendas, or philosophical biases that might have affected the conduct of the study. The study was carried out independently, and no agreements with sponsors limited access to data, analysis, interpretation, or publication. If any specific conflicts exist, they would be disclosed here. Since none exist, this statement confirms impartiality and scientific integrity.

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Ethical Approval and Informed Consent

All subjects included in the study gave informed consent to participate. Participant information was kept anonymous and in accordance with the International Committee of Medical Journal Editors (ICMJE) guidelines for the protection of research participants. This research was reviewed and approved by the Non-Interventional Clinical Research Ethics Committee of Istanbul Medipol University (Decision Number 1124, dated 28.11.2024). The study was conducted following the principles of the Declaration of Helsinki.

Authorship Statement

The author(s) have made substantial contributions to all phases of the study and are able to take public responsibility for the content and results presented in the manuscript. As the author of this study, I declare that I actively participated in the study design, data collection, analysis, interpretation, writing, and final approval of the manuscript. I take full responsibility for the accuracy and integrity of the content.

Author Contributions & Responsibilities

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Sažetak

RANO OTKRIVANJE PACIJENATA SA POVREDAMA KOJIMA JE POTREBNA INTENZIVNA NEGA U URGENTNOJ SLUŽBI: MODEL NOVE GENERACIJE ZA PROCENU RIZIKA

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Uvod: Trauma ostaje vodeći uzrok smrti širom sveta; stoga je važno identifikovati pacijente kojima je potreban prijem u jedinicu intenzivne nege (JIN) u Urgentnoj službi (US). Trenutni sistemi bodovanja traume, kao što su Glasgow Coma Scale (GCS), Revised Trauma Score (RTS) i Injury Severity Score (ISS), nisu baš efikasni u predviđanju potreba za JIN. Primena prediktivnih modela zasnovanih na mašinskom učenju (ML) je novi pristup za poboljšanje procesa trijaže.

Cilj: Primarni cilj ove studije bio je razvoj i validacija modela bodovanja rizika zasnovanog na mašinskom učenju za ranu identifikaciju pacijenata sa traumom kojima je potreban prijem u JIN iz urgentne službe. Studija je takođe imala za cilj proceniti prediktivnu sposobnost ML modela u poređenju sa tradicionalnim sistemima bodovanja kao što su GCS, RTS i ISS.

Metode: U Državnoj bolnici Esenyurt Necmi Kadıoğlu sprovedena je retrospektivna, opservaciona kohortna studija, u kojoj su prikupljeni podaci o pacijentima s traumom od 1. januara 2024. do 31. augusta 2024. godine. U studiju je uključeno 1.500 pacijenata s traumom starosti ≥ 18 godina s kompletnim kliničkim, laboratorijskim i radiološkim dijagnostičkim podacima. Prediktivne varijable sastojale su se od demografskih podataka, mehanizma traume, vitalnih znakova, laboratorijskih rezultata, radioloških dijagnostičkih nalaza i postojećih trauma skorova. Površina ispod krive (AUC), osetljivost, specifičnost, tačnost, pozitivna prediktivna vrednost (PPV) i negativna prediktivna vrednost (NPV) korišćene su za obuku i evaluaciju ML algoritama (Logistička regresija, Slučajna šuma, Mašine potpornih vektora, XGBoost i LightGBM). Model je upoređen s tradicionalnim skoring sistemima korištenjem DeLong testa.

Rezultati: Od 1500 pacijenata, 50,73% (n = 761) je zahtevalo prijem u Intenzivnu negu. Razvijeni ML model imao je AUC od 0,999, sa osetljivošću od 99,22%, specifičnošću od 99,69% i tačnošću od 99,56%, što daleko nadmašuje tradicionalne sisteme bodovanja. Najjači prediktori prijema u intenzivnu negu bili su dob, nivo laktata, RTS, sistolni krvni pritisak, frekvencija disanja i zasićenost kiseonikom. Nije uočena značajna razlika u stopama prijema u intenzivnu negu između grupa sa tupom i penetrirajućom traumom, što ukazuje na to da se sam mehanizam traume ne bi trebao koristiti kao prediktor.

Zaključak: Model bodovanja rizika zasnovan na mašinskom učenju pokazao je bolje prediktivne performanse od tradicionalnih sistema bodovanja traume u identifikaciji pacijenata sa traumom kojima je potreban prijem u intenzivnu negu. Integracija ovog modela u tokove rada Urgentnih službi može poboljšati trijažu i negu pacijenata. Međutim, pre kliničke implementacije potrebna je validacija u multicentričnim prospektivnim studijama.

Ključne reči: Mašinsko učenje, Pacijenti s traumom, Prijem u intenzivnu negu, Model bodovanja rizika, Urgentna medicina, Prediktivna analitika.

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