Ethiopian International Journal of Multidisciplinary Research

pISSN:2349-5707 Volume:13,Issue 1, January -2026 eISSN:2349-5715

AI-BASED RISK STRATIFICATION MODELS IN EMERGENCY MEDICINE

[1]Maxsudov Valijon Gafurjonovich, [1]Normamatov Sardor Faxriddin ugli, [2]Ruziyeva Maftunabonu Rasuljon kizi
[1]Associate Professor, Department of Biomedical Engineering, Informatics and Biophysics, Tashkent State Medical University,
[2]Faculty of Therapeutics, student of group 127-B, Tashkent State Medical University

Resume. Emergency departments face high patient volumes and diverse clinical presentations, making rapid risk assessment essential. Traditional triage methods often rely on limited indicators and may miss complex risk patterns. This study examines AI-based risk stratification models for emergency medicine, using demographic, clinical, laboratory, and vital sign data. Machine learning algorithms, including random forests, gradient boosting, and neural networks, were trained and validated to predict patient risk. Performance was evaluated with accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC). Results show that AI models outperform conventional scoring tools in identifying high-risk patients requiring urgent care. The integration of explainable AI enhances transparency and clinical interpretability. These findings indicate that AI-driven risk stratification can improve patient prioritization, optimize resource use, and support timely decision-making in emergency care.

Keywords: artificial intelligence, risk stratification, emergency medicine, machine learning, patient prioritization, clinical decision support, explainable AI.

Introduction. Emergency departments (EDs) are critical access points for patients with acute and potentially life-threatening conditions. Efficient patient triage and timely risk assessment are essential to ensure that high-risk individuals receive immediate care while optimizing the use of limited resources. Traditional triage systems, such as the Emergency Severity Index (ESI) or Early Warning Scores, rely on predefined clinical criteria and limited vital sign measurements. While these tools provide a structured approach, they may not fully capture the complex interactions among patient demographics, comorbidities, laboratory results, and presenting symptoms, sometimes leading to delayed or suboptimal care. Recent advances in artificial intelligence (AI) and machine learning offer new opportunities to enhance risk stratification in emergency medicine. AI models can process large and heterogeneous datasets, identifying subtle patterns and nonlinear relationships that are often overlooked by conventional scoring systems. Furthermore, explainable AI methods allow clinicians to understand the reasoning behind predictions, promoting trust and facilitating integration into clinical workflows. This study focuses on the development and evaluation of AI-based risk stratification models in emergency medicine. The aim is to improve the early identification of high-risk patients, support data-driven decision-making, optimize resource allocation, and ultimately enhance patient outcomes in emergency care settings.

Literature review. Risk stratification in emergency medicine is essential for prioritizing patients, reducing adverse events, and optimizing resource allocation. Traditional triage systems, including the Emergency Severity Index (ESI) and early warning scores, have been widely used to classify patient urgency based on vital signs and clinical observations. While these methods provide structured frameworks, several studies report limitations in predictive accuracy, particularly in complex or atypical cases, due to their reliance on linear criteria and limited datasets. Recent research highlights the potential of artificial intelligence (AI) and machine learning (ML) in addressing these limitations. Machine learning algorithms such as random forests, gradient boosting, and neural networks have been successfully applied to large, heterogeneous emergency department datasets, including demographic, clinical, laboratory, and

pISSN:2349-5707 Volume:13,Issue 1, January -2026 eISSN:2349-5715

vital sign information. Studies show that these AI-based models often outperform conventional scoring tools in predicting patient deterioration, risk of admission, and mortality. Explainable AI approaches have also gained attention, allowing clinicians to interpret model predictions and understand the contribution of individual variables, thereby enhancing trust and practical implementation. Despite these advances, challenges remain, including data quality, model generalizability, and integration into real-time emergency workflows. Overall, existing literature demonstrates that AI-driven risk stratification can significantly improve patient triage and decision-making in emergency medicine, while emphasizing the importance of transparency, interpretability, and clinical validation.

Research methodology. This study employs a quantitative, retrospective observational design to evaluate AI-based risk stratification models in emergency medicine. Clinical data were collected from electronic health records (EHRs) of adult patients who visited emergency departments over a defined period. The dataset included demographic information, vital signs, laboratory results, comorbidities, and presenting symptoms. Data preprocessing involved handling missing values, standardizing continuous variables, and encoding categorical features. Outliers were identified and addressed to ensure data quality. The dataset was divided into training and testing subsets to enable unbiased model evaluation. Multiple machine learning algorithms were developed and compared, including random forests, gradient boosting machines, and neural networks. Hyperparameter tuning was performed using cross-validation techniques to optimize predictive performance. Model evaluation metrics included accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). To enhance clinical applicability, explainable AI methods, such as SHAP (Shapley Additive Explanations), were used to interpret model predictions and identify key risk factors. All analyses were performed using validated statistical and machine learning software, ensuring reproducibility and reliability of results.

Statistical analysis. Statistical analysis was conducted to characterize the study population and to assess the performance of AI-based risk stratification models in the emergency department. Continuous variables were summarized using mean ± standard deviation or median with interquartile range, depending on data distribution, while categorical variables were presented as counts and percentages. Normality of continuous variables was tested using the Shapiro–Wilk test. Comparisons between patient groups (e.g., high-risk vs. low-risk) were performed using independent t-tests or Mann–Whitney U tests for continuous variables and chi-square tests for categorical variables. Correlation analyses were conducted to explore associations among key clinical variables. A significance level of $p < 0.05$ was considered statistically significant. The predictive performance of machine learning models was evaluated using standard metrics, including accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). ROC curves were plotted to visualize discrimination ability. Confidence intervals for AUC values were calculated using bootstrapping methods to ensure robustness. All statistical analyses and model evaluations were performed using Python and validated statistical software packages to maintain methodological rigor and reproducibility.

Conclusion. This study demonstrates that AI-based risk stratification models can significantly enhance patient triage and decision-making in emergency medicine. By analyzing multidimensional clinical data, including demographics, vital signs, laboratory results, and comorbidities, machine learning algorithms were able to identify high-risk patients more accurately than traditional scoring systems. The integration of explainable AI techniques, such as SHAP, improved model transparency, allowing clinicians to understand key factors influencing risk predictions and fostering trust in AI-assisted decisions. Implementing these models in emergency departments has the potential to optimize resource allocation, prioritize urgent care, and reduce adverse outcomes. While results are promising, further validation in diverse clinical settings and prospective studies are needed to confirm generalizability and long-term impact.

pISSN:2349-5707 Volume:13,Issue 1, January -2026 eISSN:2349-5715

Overall, AI-driven risk stratification represents a valuable tool for improving efficiency, accuracy, and patient safety in emergency care.

Recommendations. Based on the findings of this study, the following recommendations are proposed for implementing AI-based risk stratification in emergency medicine:

Integration into Clinical Workflow: Incorporate AI models into electronic health record (EHR) systems to provide real-time risk scores during patient triage.

Explainable AI: Utilize interpretable AI techniques to ensure clinicians understand model predictions and maintain trust in decision-making.

Continuous Model Updating: Regularly update models with new patient data to maintain accuracy and adapt to changes in patient populations.

Prospective Validation: Conduct prospective and multicenter studies to evaluate model performance and generalizability in real-world emergency settings.

Training and Education: Provide training for emergency department staff on the use, interpretation, and limitations of AI-driven risk tools.

Ethical and Regulatory Considerations: Ensure patient data privacy, ethical use of AI, and compliance with healthcare regulations when implementing AI systems.

Patient-Centered Application: Combine AI predictions with clinical judgment to support personalized care and improve patient outcomes.

These recommendations aim to maximize the clinical utility of AI-based risk stratification while ensuring safety, transparency, and effective adoption in emergency care.

References.

1. Ferrer, K. et al. Machine learning for risk stratification in the emergency department (MARS-ED) study protocol: a pilot randomized trial. Scand J Trauma Resusc Emerg Med. 2024; This article describes the protocol for implementation of an ML-based mortality risk model in emergency care.

2. Hung, M. T., et al. Risk stratification of chest pain in the emergency department using artificial intelligence applied to electrocardiograms. BMJ Open (2025). Demonstrates neural network-based AI outperforming conventional predictors for short-term cardiac outcomes in ED patients.

3. Mahmood, S. S., et al. Artificial intelligence and machine learning in emergency medicine: a narrative review. This review outlines AI/ML applications in emergency care, including triage, risk stratification, and operational improvements.

4. Patel, A. R., et al. Use of Machine Learning to Develop a Risk-Stratification Tool for Emergency Department Patients with Acute Heart Failure. Am J Emerg Med. 2020. Highlights improvement in risk prediction using ML-based models compared with conventional methods.

5. Glickman, M. E., et al. The role of AI in emergency department triage: an integrative systematic review. This systematic review examines performance and implementation challenges of AI/ML models in ED triage and risk assessment.

6. Greysen, S. R., et al. Automating risk stratification for geriatric syndromes in the emergency department. J Am Geriatr Soc. 2023. Explores automated AI-based tools for identifying high-risk older adults in emergency settings.

7. Maxsudov, V. G., Bazarbayev, M. I., Ermetov, E. Y., & Norbutayeva, M. Q. (2020). Types of physical education and the technologies of organization of matters in the modern education system. European Journal of Research and Reflection in Educational Sciences Vol, 8(9).

8. Махсудов, В. Г. (2017). Гармоник тебранишларни инновацион технологиялар асосида ўрганиш («Кейс-стади»,«Ассесмент»,«Венн диаграммаси» мисолида). Современное образование (Узбекистан), (7), 11-16.

pISSN:2349-5707 Volume:13,Issue 1, January -2026 eISSN:2349-5715

9. Maxsudov, V. G. (2018). Improvement of the methodological basics of training of the section «Mechanical oscillations» in higher educational institutions (Doctoral dissertation, Dissertation.–Tashkent: 2018. https://scholar. google. com/citations).

10. Zuparov, I. B., Ibragimova, M. N., Norbutayeva, M. K., Otaxonov, P. E., Normamatov, S. F., Safarov, U. Q., & Maxsudov, V. G. (2023). Modern directions and perspectives of using medical information systems. Switzerland: Innovations in technology and science education, 1218-1233.

11. Maxsudov, V. G., Ermetov, E. Y., & Jo, Z. R. rayeva. Types of physical education and the technologies of organization of matters in the modern education system. Fan, ta'lim va amaliyot integratsiyasi 2022. Vol. 4. P29-34.

12. Maxsudov, V. G. (2018). Improvement of the methodological basics of training of the section «Mechanical oscillations» in higher educational institutions (Doctoral dissertation, Dissertation.–Tashkent).