Early mortality risk prediction in acutely injured service members using machine learning algorithms

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Abstract: Traumatic injury remains the leading cause of death among individuals under 45 years of age. Many of these deaths are potentially preventable with timely diagnosis and intervention. Early accurate prediction of mortality risk is critical for guiding life-saving decisions in both military and civilian trauma settings. However, there remains a significant unmet need for rapid, reliable assessment tools that can be deployed in medical treatment facilities (MTFs), combat support hospitals, and civilian trauma centers. Machine learning (ML) algorithms have shown promise in predicting clinical outcomes. This study aimed to identify ML models with the best diagnostic performance of multiple ML models in predicting in-hospital mortality among injured patients in both military and civilian populations.

This retrospective observational study analyzed data from the Department of Defense Trauma Registry (DoDTR), including 32,735 U.S. service members (SMs) injured between January 1, 2003, and December 31, 2023. Thirty-seven features were selected for model development, encompassing demographics, injury characteristics (mechanism and type of injury, injured body region, injury severity score, TRISS, revised trauma score), vital signs, and other clinical variables. Six ML models – decision tree (DT), gradient boosting (GB), logistic regression (LR), neural network (NN), random forest (RF) and support vector machine (SVM) – were trained to predict in-hospital mortality. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC) and Kolmogorov-Smirnov (KS) statistics for the best diagnostic performance for predicting mortality in trauma patients, especially in the battlefield, ensuring a comprehensive and rigorous approach to the analysis.

Among 31,206 SMs who arrived at an MTF alive, 592 (1.9%) died in-hospital or died of wounds. The AUC scores for DT, GB, LR, NN, RF, and SVM were 0.949, 0.980, 0.807, 0.723, 0.985, and 0.935, respectively. Corresponding KS values were 0.838, 0.886, 0.606, 0.417, 0.901, and 0.736, respectively. The random forest model emerged as the champion model with superior AUC and KS values. The five most influential predictors across all models were Glasgow Coma Scale (GCS), systolic blood pressure (SBP), injury severity score (ISS), shock index, and head injury.

Understanding the risk factors that contribute to mortality risk in combat-injured service members is essential for improving survivability. The random forest model emerged as the most accurate and reliable ML approach, offering high predictive performance without overfitting. These findings highlight the potential of ML-based tools to enhance trauma care and reduce mortality in both military and civilian settings. This work represents a significant step toward the development of deployable, data-driven decision support systems in trauma medicine.

ACKNOWLEDGEMENTS

This work was supported by the Trauma Research and Combat Casualty Care Collaborative (TRC4).

Keywords: Mortality prediction; machine learning; combat casualty care; trauma outcomes; military medicine.

