Algorithms to Identify and Differentiate Shock in Combat Casualties

Yuliya Pinevich, MD;[1] Adam Amos-Binks, PhD;[2] Christie S. Burris;[2] Gregory Rule;[2] Ryan Lowe;[2] Brian W. Pickering, MB, BCh, MSc;[1] Christopher P. Nemeth, PhD;[2] Vitaly Herasevich, MD, PhD[1]

1. Mayo Clinic, Rochester, MN
2. Applied Research Associates, Inc., Albuquerque, NM

Abstract (50-75 words)
Circulatory shock is a potentially deadly condition characterized by inadequate cellular oxygen metabolism and rapidly emerging multi-organ failure. The survival rate for patients with circulatory shock is determined by timely recognition of shock onset and timely identification of underlying cause by combat medics. Use of machine learning (ML) can boost medics' ability to analyze medical data while performing tactical combat casualty care (TCCC) in austere battlefield settings. This work is the first step toward the development of a decision support system using machine learning algorithms to detect and differentiate shock.

Introduction
Delay in evacuation during prolonged field care (PFC) in the austere setting of a battlefield is likely to lead to patients presenting with various complications such as infection or slow internal bleeding that could lead to shock. Healthcare providers' experience and skills to recognize types of shock other than hypovolemic may be substantially limited. The Trauma Triage, Treatment, and Training Decision Support (4TDS) project is developing a decision support system for medics and clinicians. The objective of this study is to develop models based on Electronic Medical Records (EMR) data to create 4TDS algorithms that can identify and differentiate among possible types of shock.

Methods
An IRB-approved study was conducted at Mayo Clinic in Rochester, MN, and involved all patients ≥18 years old admitted to the intensive care unit (ICU) in the 3 years spanning 2015 through 2018. EMR data, including demographics, vital signs, nursing flowsheets, laboratory values, and medications were extracted. Using a combination of clinical diagnoses and ICD codes, patients were labeled with their corresponding shock diagnosis (i.e., cardiogenic, septic, hypovolemic). Administration of vasopressors and abnormal lactate labs served as a so-called "diagnosis proxy time". A window of 120 minutes around the diagnosis proxy time was isolated for each patient offset by 15 minute intervals to afford a prognostic model. ML models were trained on labeled data that were comprised of 70 EMR features, including temporal trends of selected vital signs. The qualifying outcome event was either shock (for detection component of algorithm), or hypovolemic shock, septic shock, or cardiogenic shock (differentiation component of algorithm). The dataset was randomly divided into testing and training cohort using 5-fold cross validation, and corresponding performance measures were recorded.

Results
Electronic medical record data were extracted from 18,349 ICU patients, including a total of 1,155 those with cardiogenic (6.3%), 521 hypovolemic (2.8%) and 1,465 septic (8.0%) shock. A total of 1866 cases were used for model development. Logistic regression was used to create an algorithm detection component. During algorithm training, the shock detection model showed an area under curve (AUC) for the qualifying outcome event "shock" of 0.84. During algorithm testing the validation cohort demonstrated a sensitivity of 73% and specificity of 80%, positive predictive value (PPV) of 25%, and negative predictive value (NPV) of 97%. Shock differentiation models showed: 1) AUC of 0.85 for septic shock with sensitivity of 63% and specificity of 82%, and positive predictive value PPV of 12% and NPV of 98%; 2) AUC of 0.82 for cardiogenic shock with sensitivity of 67% and specificity of 82%, and positive predictive value PPV of 10% and NPV of 99%; 3) AUC of 0.71 for hypovolemic shock with sensitivity of 46% and specificity of 79%, and positive predictive value PPV of 3% and NPV of 99%.

Conclusion
The machine learning algorithms can identify different types of shock with moderate accuracy before a shock event has happened and can be used as part of a pre-hospital combat casualty decision support system. A prospective real time trial is scheduled at Mayo Clinic, Rochester, MN to compare decision support system performance to standard of care.