Predicting Observable and Occult Injuries in Trauma Patients from Sparse Measurements

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Abstract. Trauma patients suffer a wide variety of injuries which can be both observable and unobservable (i.e., occult). Early identification can be critical in effective treatment and even preventing death. Unfortunately, highly trained medical staff and sophisticated diagnostic equipment capable of accurately diagnosing these injuries are often unavailable at the site of injury. An automated system for assisting first responders in diagnosing traumatic injury is needed. Some injuries can be statistically associated with basic observable traits, but the sheer volume of trauma patient data makes it virtually impossible to manually parse and glean useful information. Machine learning techniques allow the efficient mining of these data sets to pull in correlations and patterns which can be exploited. We propose a machine learning enabled injury prediction tool, capable of being used by minimally trained trauma responders, on a mobile device, using only easily obtained patient information.

Keywords: trauma care, machine learning, healthcare decision systems

1 Introduction

Injuries are a critical health concern around the world, ten percent of all humans deaths - almost 5 million annually - are attributable to injury [6]. In areas where extensively trained physicians have access to high fidelity patient data, accurate injury diagnosis is often possible. However, in scenarios where advanced healthcare is not available (e.g., combat zones, low to moderate income countries (LMIC), and post-natural disaster areas), the results are not nearly as favorable. In these scenarios, first responders, or even primary medical staff, may not have a sufficient depth of training or the advanced diagnostic equipment available allowing the accurate diagnosis of the full range of injuries in a patient. Fortunately, many of the patient's basic metrics are attainable even in these scenarios; for example, heart rate, blood pressure, Glasgow Coma Score, mechanism and location of injury (we shall refer to these as the Admission Metrics (AMs)),are capable of being obtained by most first responders.

The availability of rich Electronic Health Records (EHR), has made learning correlations between measured patient features (e.g., heart rate, breathing rate, method of injury) and injuries possible. Traditionally, EHR are leveraged in automated tools by having a domain expert designate patterns to look for on an injury-by-injury basis and to specify clinical variables in an ad-hoc manner [3]. Unfortunately, manually probing vast, high dimensional EHR for correlations and predefined patterns to make predictions may be not be possible. Therefore, we turn to modern data-driven approaches capable of automatically unveiling these patterns.

2 Approach

In this work, we introduce a Machine Learning (ML) enabled tool to assist in traumatic injury prediction using sparse patient data capable of being attained from minimally trained trauma responders; sparse, in this case, refers to a relatively low quantity of measurements on the patient. ML-enabled systems are playing an increasingly prominent role throughout our society, and are beginning to percolate into the healthcare sector [5]. ML provides means to exploit large EHR data sets and provides a set of tools to allow the mining of patterns too complex to extract by manual means. Specifically, we are interested in classifying injuries with support vector machines (SVM), deep neural net, and decision tree ML classifiers using AMs; the relatively low computational requirements for these classifiers enable them to be easily deployed on a mobile device that can be used at the site of injury. Initial statistical results of the multiclass and multi-label classification problem are generated and discussed in Section 4.

To refine the scope of the tool, we select occult and visible vascular injuries, and solid organ injuries. The reason for selecting these injuries is threefold: 1) There has been an increase in the incidence of these injuries in the United States that has paralleled the increase in assault with firearms, motor vehicle crashes, and invasive medical procedures [1]; 2) In one major review of battlefield mortalities, it was found that 24.3 % of vascular injury related death were preventable [2]; and 3) In multi-trauma patients, the presence of vascular injury was associated with increased mortality in less severely injured patients [4]. Modern medical treatment centers keep detailed EHR on not only the injury, but a multitude of patient metrics, producing volumes of detailed data sets. When examining vascular trauma, correlations began to emerge in the data between the injury and the AMs- the presence of these broad correlations demonstrates there exists fertile ground for analysis between trauma patient characteristics, and traumatic injury.

3 Data

The initial goal was to test the feasibility of our approach by demonstrating that trauma related injuries can be predicted using basic AMs. To act as a training and testing pool, we employ data from the Trauma Registry maintained by the

R. Adams Cowley Shock Trauma Center of the University of Maryland (STC). While the total database includes almost seventy thousand patients, we selected a subset of patients known to the division of vascular surgery over a nine-year period, consisting 2,643 distinct patients. The injury types, quantities, and AIS codes are listed in Table I. The features used were numerical representations of: injury type (blunt, penetrating, crushing), protective equipment (yes or no), Abbreviated Injury Scale (AIS), Glasgow Coma Scale score, and region of injury.

4 Results

Initial testing was performed using 5-fold cross validation, where the we randomly up-sampled the data to account for the imbalance in injuries. Training and testing sets are intentionally disjoint (i.e. no single individual was used both for training and testing). The classification problem was cast as a multiclass and multilabel problem; to this end, we learned individual models for SVM, KNN, and decision trees for each injury. In the testing portion, the input features for each test patient were passed into the model and a *yes* or *no* decision was determined for each injury. Although we performed classification via SVM, KNN, deep neural networks and decision trees, we present only the result for decision trees as they were superior in classification performance. We present the summary statistics in Table 1.

Summary Statistics						
Injury	AIS Code	Sensitivity	Specificity	Precision	F1 Score	Occurrences
Diaphragm Laceration	440604.3	0.90	0.81	0.59	0.851	116
Lung Contusion Unilateral	441406.3	0.96	0.67	0.64	0.876	344
Thorax Contusion	410402.1	0.79	0.68	0.57	0.786	190
Lung Contusion Bilateral	441410.4	0.99	0.84	0.69	0.769	250
Lung Laceration	441430.3	0.79	0.76	0.58	0.782	154
Rib Cage Frac. w/ hemo	450222.3	0.97	0.66	0.56	0.780	127
>1 Rib Cage Frac. w/ hemo	450252.4	1.0	0.77	0.58	0.861	122
Liver Laceration < 3cm	541822.2	0.98	0.70	0.56	0.772	98
Liver Laceration > 3cm	541824.3	0.98	0.78	0.56	0.822	85
Spleen Laceration < 3cm	544222.2	0.98	0.72	0.56	0.819	101
Spleen Laceration	544226.4	0.99	0.92	0.65	0.920	86
Upper Extremity Laceration	721008.3	0.96	0.91	0.66	0.794	125

Table 1. Classification results for the 12 most commonly occurring injuries in our data.

5 Conclusion and Outlook

Given the successful results of the initial experiments, this potentially opens the door for developing a helpful screening tool to assist first responders and medical staff where advanced training and sophisticated diagnostic equipment does not exist or is unavailable. Further work is required: a thorough set of tests in a clinical setting on the validity of the method, validating the results on a new testing/training set, and an exploration of to methods to enhance the performance should be considered. To begin the formal validation process, we have made arrangements for a usability study conducted by Med Star.

The applications of such a prediction tool are far reaching. For example, using TensorFlow Mobile, we have developed an injury diagnosis Android application leveraging our learned decision tree models. First responders, combat medics, and disaster relief medical staff could be equipped with such an app to assist them in making informed diagnoses and emergency treatment for victims of trauma, without extensive training or resources. Basic instructions could be appended to the diagnosis, such as tourniquet application, which could further eliminate easily preventable fatalities.

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