SuperLearner versus Clinicians to Prioritise Trauma Patients (working title)

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Abstract

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Author Summary

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Introduction

Trauma is a major threat to population health globally [1, 2]. Every year about 4.6 million people die because of trauma - a number that exceeds the total number of yearly deaths from HIV/AIDS, malaria and tuberculosis combined. The most common cause of trauma is road traffic injuries (RTIs); in 2016 an estimated 1.3 million people died from RTIs alone [2]. Global actors have vowed to try to halve the number of deaths from road trauma by 2020, but this sustainable development goal is far from being realized [3]. This situation calls for not only more interventions, but also strengthened research on effective trauma care delivery.

Trauma care is highly time sensitive and delays to treatment has been associated with increased mortality across settings [4–6]. Early identification and management of potentially life threatening injuries is crucial for survival. A key component of trauma care is therefore the process of prioritizing patients to match level of care with clinical acuity [7, 8]. The existing literature on how to prioritise trauma patients focuses largely on two issues. First, in the prehospital setting the main focus has been to idenfity patients who merit transfer to a trauma centre [9]. Second, in the hospital setting a substantial body of research has focused on the appropriate criteria for trauma team activation [10, 11].

Although both these issues are important, clinicians all over the world are on a daily basis faced with the more complex problem of how to decide in what order to assess and treat trauma patients that arrive to the emergency department (ED). In health systems with formalised criteria for prioritizing ED patients, all patients are assigned a priority coupled with a target time to treat. These priorities are may be coded using colors, for example red, orange, yellow and green, with red being assigned to the most urgent patients and green to the least urgent [12], or numbers [13].

In health systems without formalized criteria, for example in many low resource settings, clinician gestalt is used informally to prioritize among trauma patients arriving to the ED [14]. As there is commonly no formal prehospital care systems in such settings, trauma patients often arrive to the ED without warning and without any form of previous prioritisation to guide the appropriate level of care in hospital [15]. Also, mass casualties may occur frequently, especially in RTIs. Identifying ways to quickly prioritize the patients in need of more immediate care would therefore be very valuable in a many low resource settings.

In contrast to trauma centre transfer or trauma team activation, the approach to prioritization among trauma patients arriving to the ED has received little attention from the research community. Framed as a classification problem this challenge can be addressed using a statistical learner. Logistic or proportional hazards models are common classification learners whereas more modern alternatives include random forests or convolutional neural networks. These learners all exist along the machine learning spectrum governed by their relative "human-to-machine decision-making-effort", with regression learners in the more-human-than-machine (MHTM) end and networks at the other, more machine than human (MMTH), end of the spectrum [16].

The application of MMTH learners to solve classification problems in medicine is not new [17], but the uptake and use of such learners in trauma research has been slow [18]. Some studies have approached the trauma centre transfer and trauma team activation issues using MMTH learners, and the results are conflicting with regards to the superiority of such learners over MHTM learners or standard criteria [19–22]. One very recent study used a random forest learner to assign priority to patients in a general ED population, and found a slight performance improvement using this MMTH learner compared to the standard criteria [23].

Thus, there seems to be a paucity of reseach on how to leverage machine learning to prioritise among trauma patients in the ED. Therefore, we set out to conduct a benchmark study, in which we attempted to improve on what we considered the two most important limitations of previous related research, namely the use of retrospective data and the focus on one specific MHTM or MMTH learner. We aimed to compare the performance of an ensemble machine learning methodology called SuperLearner to that of clinician gestalt based on patients' presentation. Our hypothesis was that the performance of the SuperLearner would be non-inferior to that of clinician gestalt.

Materials and Methods

Study Design

We used data from an ongoing prospective cohort at three public hospitals in urban India. Our analysis is an adjunct to a registered observational study to compare the performance of clinical prediction models with clinicians (ClinicalTrials.gov identifier NCT02838459).

Study Setting

Data anlysed for this study came from patients enrolled between 28 July 2016 and 21 November 2017 at the three hospitals Khershedji Behramji Bhabha hospital (KBBH) in Mumbai, Lok Nayak Hospital of Maulana Azad Medical College (MAMC) in Delhi, and the Institute of Post-Graduate Medical Education and Research and Seth Sukhlal Karnani Memorial Hospital (SSKM) in Kolkata. The time frame was decided to ensure that all included patients had completed six months follow up. KBBH is a community hospital with XX inpatient beds. There are departments of surgery, orthopedics and anesthesia. It has a general ED where all patients are seen. Most patients present directly and are not transferred from another health centre. Plain X-rays and ultrasonography are available around the clock but computed tomography (CT) is only available in-house during day-time. During evenings and nights patients in need of a CT are referred elsewhere. MAMC and SSKM are both university and tertiary referral hospitals. This means that all specialities and imaging facilities relevant to trauma care, except emergency medicine, is available in-house around the clock. MAMC has approximately 2200 inpatient beds and SSKM has around XX inpatient

beds. MAMC has a general ED whereas SSKM has two EDs, one where patients with suspected or confirmed neurosurgical conditions are seen and one where patients with other acute conditions are seen. The rationale for this setup is that SSKM is the only referral centre for neurosurgical care in the Kolkata metropolitan area, which has a population of close to 15 million people. Because both MAMC and SSKM are tertiary referral hospitals a majority of patients arriving at their EDs are transferred from other health facilities, with almost no transfer protocols in place. Prehospital care is rudimentary in all three cities, with no organised emergency medical services. Ambulances are predominatly used for inter-hospital transfers and most patients who arrive directly from the scene of the incident are brought by the police or in private vehicles. Patients arriving to the ED are at all centres first seen by a casualty medical officer on a largely first come first served basis. There is no formalised system for prioritising ED patients at any of the centres.

Data Collection

Data was collected by one dedicated project officer at each site. The project officers all had a masters degree in life sciences. They worked five eight hour shifts per week so that mornings, evenings and nights were covered according to a rotating schedule. In each shift, project officers spent approximately six hours collecting data in the ED and the remaining two following up patients. The collected dat awas then transferred this data to a digital database. The rationale for this setup was to ensure collection of high-quality data from a representative sample of trauma patients arriving to the EDs at participating centres, while keeping to the projects budget constraints.

Participants

Eligibility criteria

Any person aged $\geq$ 18 years or older and who presented alive to the emergency department (ED) of participating sites with history of trauma was included. The age cutoff was chosen to align with Indian laws on research ethics and informed consent. We defined history of trauma as having any of the external causes of morbidity and mortality listed in block V01-Y36, chapter XX of the International Classification of Disease version 10 (ICD-10) codebook as primary complaint, with some exclusions (Supplementary material). These causes were excluded because they are not considered trauma at the participating centres.

Source and methods of selection of participants and follow up

The project officers enrolled the first ten consecutive patients who presented to the ED during each shift. The number of patients to enrol was set to ten to make follow up feasible. A follow-up was completed by the project officer 30 days after participant arrived at participating hospital. The follow-up was completed in person or on phone, depending on whether the patient was still hospitalised or if the patient had been discharged. Phone numbers of one or more contact persons, e.g. relatives, were collected on enrollment and contacted if the participant did not reply on follow up. Only if neither the participant nor the contact person answered any of three repeated phone calls was the outcome recorded as missing.

Variables, Data Sources and Measurement

Patient characteristics and SuperLearner variables

The dependent variable, or label, used to train the SuperLearner was all-cause 30 day mortality, defined as death from any cause within 30 days of arrival to a participating centre. These data were extracted from patient records if the patient was still in hospital 30 days after arrival, or collected by calling the patient or a patient representative if the patient was not in hospital.

The independent variables, or features, included patient age in years, sex, mechanism of injury, type of injury, mode of transport, transfer status, time from injury to arrival in hours. The project

officers collected data on these features by asking the patient, a patient representative, or by extracting the data from the patient's file. Sex was coded as male or female. Mechanism of injury was coded by the project officers using ICD-10 after completing the World Health Organization's (WHO) electronic ICD-10-training tool [24]. The levels of mechanism of injury was collapsed for analysis into transport accident (codes V00-V99), falls (W00-W19), burns (X00-X19), intentional self harm (X60-X84), assault (X85-X99 and Y00-Y09), and other mechanism (W20-99, X20-59 and Y10-36). Type of injury was coded as blunt, penetrating, or both blunt and penetrating. Mode of transport was coded as ambulance, police, private vehicle, or arrived walking. Transfer status was a binary feature indicating if the patient was transferred from another health facility or not.

The features also included vital signs measured on arrival to the ED at participating centres. The project officers recorded all vital signs using hand held equipment, i.e. these were not extracted from patient records, after receiving two days of training and yearly refreshers. Only if the hand held equipment failed to record a value did the project officers extract data from other attached monitoring equipment, if available. Systolic and diastolic blood pressure (SBP and DBP) were measured using an automatic blood pressure monitor (OMRON HEM-7130-L). Heart rate (HR) and peripheral capillary oxygen saturation (SpO^2) were measured using a portable non-invasive fingertip pulse oximeter (ChoiceMMed MD300 C2D). Respiratory rate (RR) was measured manually by counting the number of breaths during one minute. Level of consciousness was measured using both the Glasgow coma scale (GCS) and the Alert, Voice, Pain, and Unresponsive scale (AVPU). GCS has three components, called the eye, verbal, and motor components. Each component indicates the response of the patient to no, voice or painful stimuli. The eye component ranges from one to four, where four indicates that the patient opens his or her eyes spontaneously (best response) whereas one indicates that the patient does not open eyes regardless of stimuli (worst response). The verbal and motor responses are graded similarly, but ranges between one to five and one to six respectively. All components also include a non-testable level. In assigning GCS the project officers used the official Glasgow Coma Scale Assessment Aid [25]. AVPU simply indicates whether the patient is alert, responds to voice stimuli, painful stimuli, or does not respond at all.

The rationale for including these specific features were that they can be reasonably exptected to be available when a trauma patient arrives to the ED. They, or some variation thereof, represent standard variables collected in more or less all health systems. They are also included in the most well know clinical prediction models designed to predict trauma mortality [26].

Clinicians' priorities

For the purpose of this study, clinicians were instructed by the project officers to assign a priority to each patient. The priority levels were color coded. Red was assigned to the most serious patients that should be treated first. Green was assigned to the least serious patients that should be treated last. Orange and yellow were intermediate levels, where orange patients were less serious than red but more serious than yellow and green whereas yellow patients were less serious than red and orange patients but more serious than green patients. The clinicians were allowed to use all information available at the time when they assigned these variables, which was as soon as they had first seen the patient. The priorities were not used to guide further patient care and no interventions were implemented as part of the study for patients assigned to the more urgent priority levels.

Bias

Remains to be written.

Quantitative Variables

All quantitative features (age, SBP, DBP, HR, SpO^2, and RR) were treated as continuous.

Qualitative Variables

The levels of all qualitative variables (sex, mechanism of injury, type of injury, mode of transport, transfer status, and GCS components) were treated as buckets (dummy variables).

Statistical Methods

We used R for all analyses [27]. We first made a non-random temporal split of the complete data set into a training and test set. The split was made so that 75% of the complete cohort was assigned to the training set and the remaining 25% to the test set, ensuring that the relative contribution of each centre was maintained in both sets. We then calculated descriptive statistics of all variables, using medians and interquartile ranges (IQR) for continuous variables and counts and percentages for qualitative variables.

Development of the SuperLearner

We then developed our SuperLearner in the training set using the SuperLearner R package [28]. SuperLearner is an ensemble machine learning algorithm, meaning that it uses a library of techniques or specific learners, in principle any technique or learner that the analyst wants, to come up with an "optimal learner". Our library included techniques suitable for predicting a binary outcome such as all cause 30-day mortality (Will add table). The SuperLearner was trained using ten fold cross validation. This procedure is implemented by default in the SuperLearner package and entails splitting the development data in ten mutually exclusive parts of approximately the same size. All learners included in the library are then fitted using the combined data of nine of these parts and evaluated in the tenth. This procedure is then repeated ten times, i.e. each part is used once as the evaluation data, and is intended to limit overfitting and reduce optimism.

Assigning Priority Levels using the SuperLearner Prediction

The SuperLearner was then used to assign levels of priority to the patients in the training set. This was done by binning the SuperLearner prediction into four bins using cutoffs identified using a grid search across all possible combinations. These bins corresponded to the green, yellow, orange, and red levels of priority assigned by the clinicians'. The performance of both the continuous and bucketed SuperLearner predictions in the training set was then evaluated using the area under the receiver operating characteristics curve (AUROCC). We then used the SuperLearner to predict the outcomes of the patients in the test set and used the cutoff values from the training set to assign a level of priority to each patient in this set.

Comparing the SuperLearner and Clinicians

The perfomance of the continous and bucketed SuperLearner predictions, as well as the clinicians, was then evaluated by estimating their AUROCC. The levels of priority assigned by the SuperLearner and clinicians respectively were then compared by estimating the net reclassification, in events (patient with the outcome, i.e. who died within 30-days from arrival) and non-events (patient without the outcome) respectively. The net reclassification in events was defined as the difference between the proportion of events assigned a higher priority by the SuperLearner than the clinicians and the proportion of events assigned a lower priority by the SuperLearner than the clinicians. Conversely, the net reclassification in non-events was defined as the difference between the proportion of non-events assigned to a lower priority by the SuperLearner than the clinicians and the proportion of non-events assigned a higher priority by the SuperLearner than the clinicians.

We used an emperical bootstrap with 1000 draws of the same size as the original set to estimate 95% confidence interval (CI) around differences. We concluded that the SuperLearner was non-inferior to clinicians if the 95% CI of the net reclassification in events did not exceed a pre-specified level of -0.05, indicating that clinicians correctly classified 5 in 100 events more than the SuperLearner.

Handling of missing data

Observations with missing data on all cause 30-day mortality or priority level assigned by clinicians were excluded. Missing data in features was treated as informative. For each feature with missing data we created a missingness indicator, a variable that took the value of 1 if the feature value was missing and 0 otherwise. Missing feature values were then replaced with the median of observed data for quantitative features and the most common level for qualitative features. We included the missingness indicators as features in the SuperLearner.

Results

During the study period, we approached a total of 5670 patients for enrollment. 215 patients did not provide informed consent. Out of the 5455 patients who provided informed consent, 215 had missing data on priority level assigned by clinicians, leaving 5455 patients. An additional 901 were excluded because of missing outcome data. Thus, the final study sample included 4554 patients.

Table 1 shows sample characteristics. The median age among included patients was 32 (IQR 24-45) years. A majority, 3554 (78%) patients, were males. The most common mechanism of injury was transport accidents, accounting for 1934 (42%) patients. A total of 1980 (44%) patients were transported to participating centres in some sort of private vehicle, such as a car, taxi, or rickshaw. A majority of patients had normal vital signs on arrival to participating centres. Out of all patients, 409 (9%) died within 30 days of arrival. The number of patients in the training and test samples were 3415 and 1139 respectively.

The AUROCC of the continuous SuperLearner prediction in the training sample was 0.9866 (Figure 1A). Figure 2A shows the agreement between the continuous predictions and observed outcomes in the training sample. The cutpoints identified by the grid search were 0.05, 0.07, and 0.59. We used these cutpoints to bin the continuous SuperLearner prediction into the four priority levels green, yellow, orange, and red. The AUROCC of the binned SuperLearner predictions in the training sample was 0.9839. Table 2 shows the number of patients and all cause 30-day mortality in each group.

We then applied the SuperLearner to the test sample. The AUROCC of the continous Super-Learner prediction was 0.9883 Figure 1B. Figure 2B shows the agreement between the continuous predictions and observed outcomes in the test sample. We used the same cutpoints as in the training sample to bin the continuous predictions into the four priority levels. The AUROCC of the binned SuperLearner predictions in the test sample was 0.9647. Table 3 shows the number of patients and all cause 30-day mortality in each group.

In the test sample we compared the performance of the binned SuperLearner prediction with that of clinicians. The AUROCC of priority levels assigned by clinicians was 0.8707. Table 4 shows the priority levels assigned by clinicians and the all cause 30-day mortality in each group. The difference in AUROCC between the binned SuperLearner prediction and clinicians was -0.0940 (95% CI -0.1501 - -0.0698). The net reclassifciation in events and non-events were 0.0246 (95% CI 0.0250 - 0.0567) and 0.3205 (95% CI 0.1822 - 0.2516) respectively. The overall reclassification is show in Table 5. Figure 3 shows the all cause 30-day mortality across priority levels assigned by the SuperLearner and clinicians.

Discussion

Our results indicate that using an ensemble machine learner developed with the SuperLearner to prioritise among adult trauma patients in the ED is non-inferior to that of clinician gestalt. In fact, our results suggest that the ensemble learner is superior to clinician gestalt, both in terms of classification and discrimination. We have not been able to identify any previous study that has applied machine learning to prioritise among trauma patients in the ED. Hence, as far as we know

Figure 1: Receiver operating characteristics curves in training (A) and test (B) samples

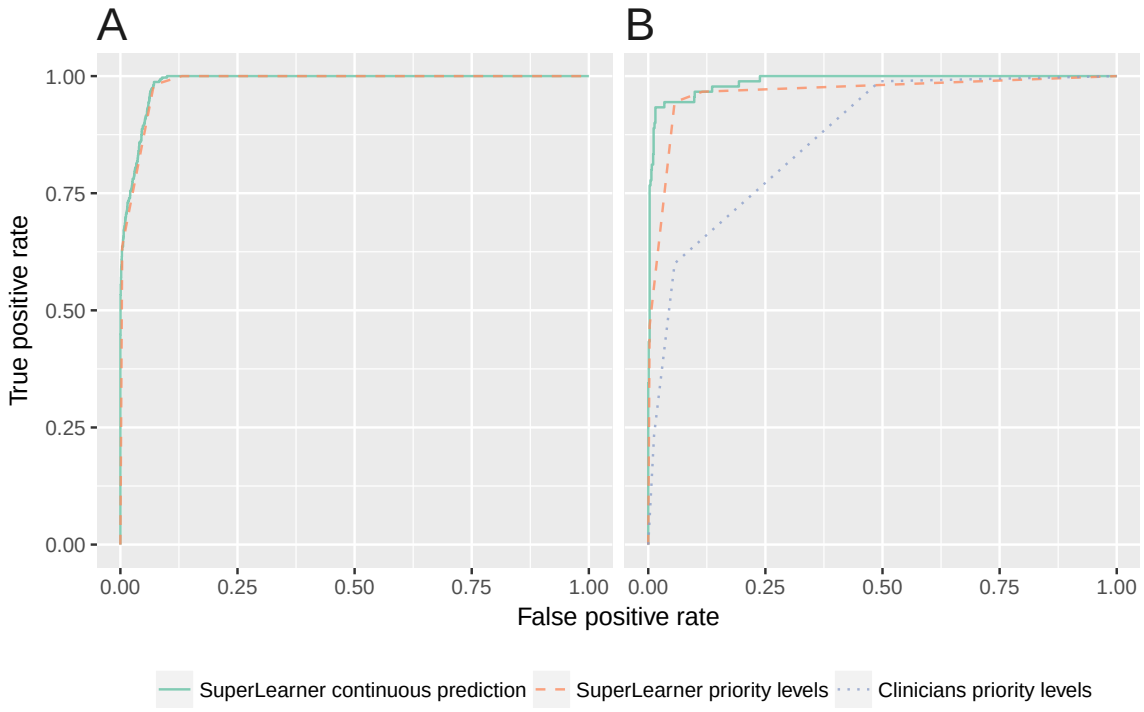
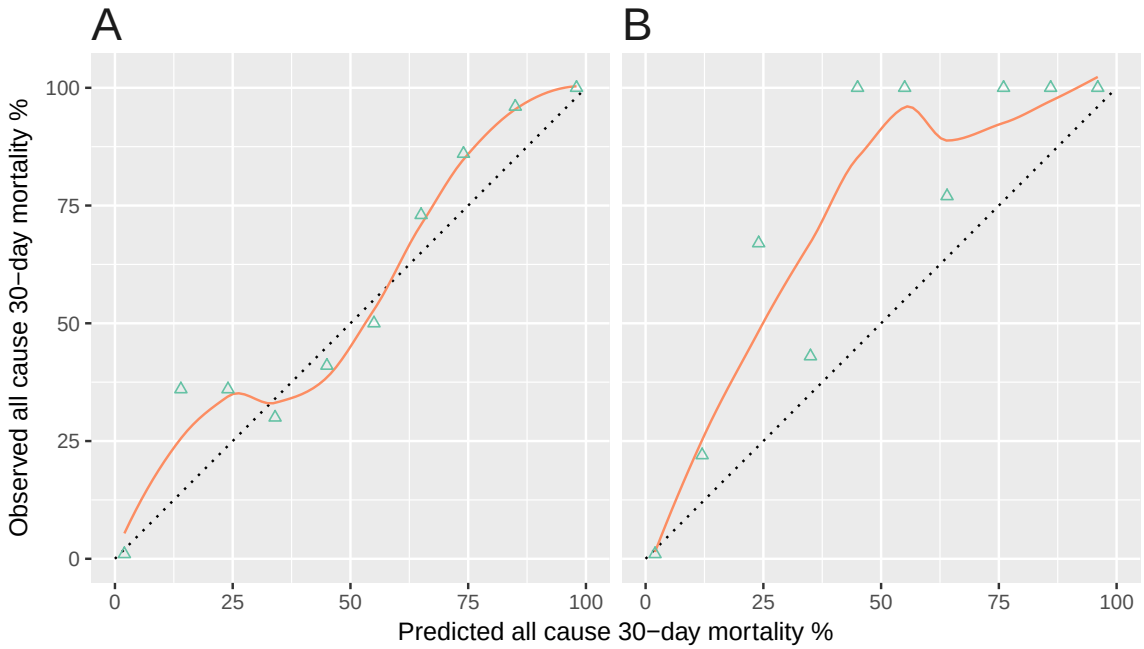
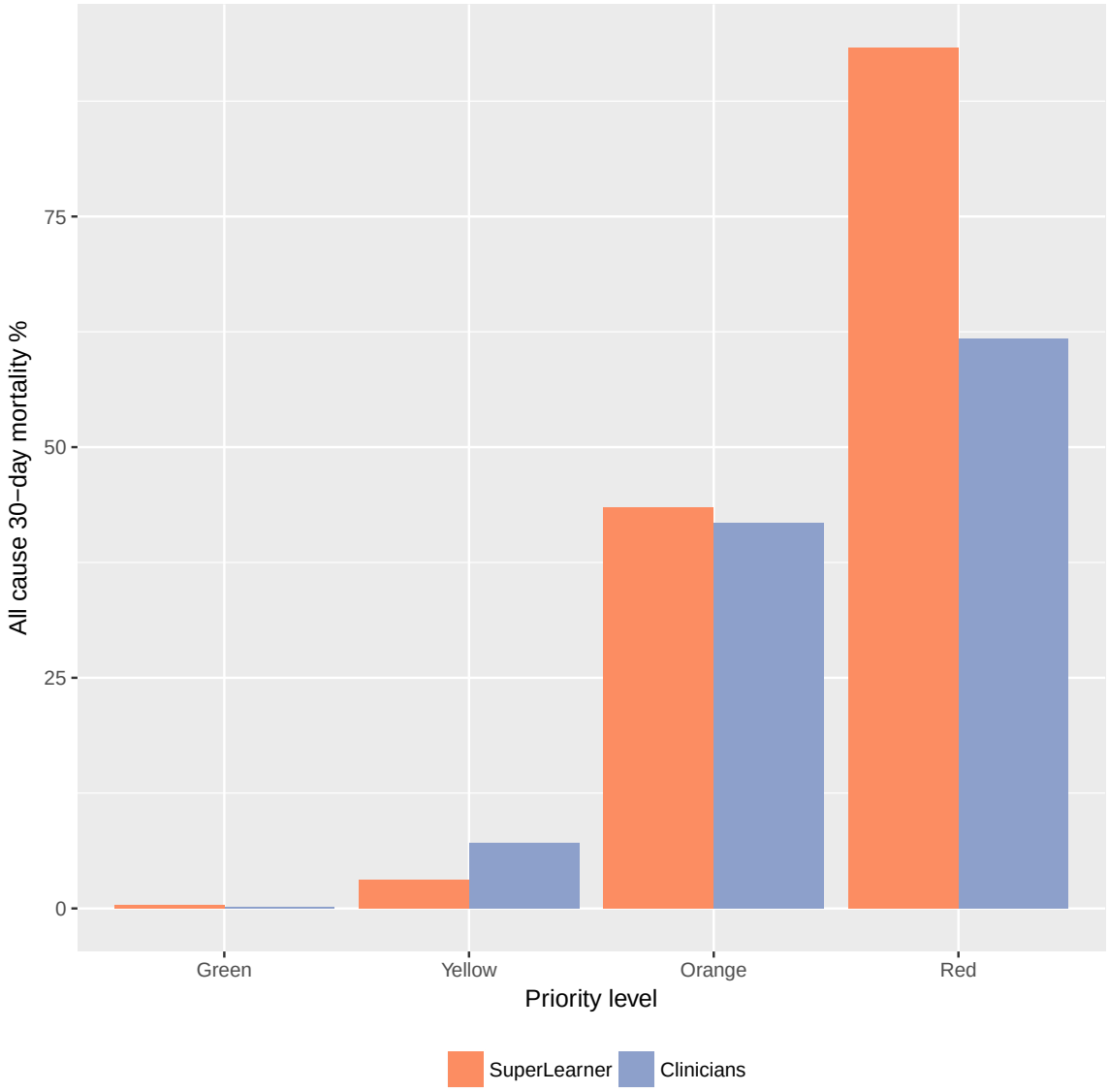


Figure 2: Agreement between the continuous SuperLearner prediction and observed all cause 30-day mortality in the training (A) and test (B) samples.



The straight dotted line indicates perfect agreement. The solid orange line is a smoothed association between mean mortality and mean predicted mortality across deciles of predicted mortality. The triangles are mortality point estimates across the same deciles.

Figure 3: All cause 30-day mortality across priority levels in the test sample



this is the first study of its kind in this area and we hope that our results can work as benchmarks to which future work can be compared.

Our study was limited by the relatively small sample size. For example, we did not have enough data to run centre wise analysis, which should be a focus of future studies. Instead we concentrated on data quality and had dedicated project officers record all data. This resulted in very low levels of missing feature data. In contrast, we did have a considerable amount of missing outcome data, about 20% of patients were lost to follow up. We handled this missingness using list wise deletion, aware of the potential bias introduced by this approach. One alternative would have been to use multiple imputation to replace missing values, however we had no way of determining the mechanism underlying the missing outcomes why results based on multiple imputed data might be biased as well. Further, we did not consider it computionally feasible to combine multiple imputation and bootstraping for uncertainty estimation. We do however consider it a strength of our study that the outcome included out of hospital deaths, when comparably recent research does not [23, 29].

We used point measurements to train the ensemble learner, meaning that we failed to account for potential changes in patients' clinical condition between the time when feature and outcome data were collected. The clinicians were however also limited to the data available when they decided on a priority level, although this could have included laboratory or imaging findings from a transferring health facility. Future research may improve the predictions by both the ensemble machine learner and clinicians by including data from multiple time points.

As opposed to the clinicians the ensemble learner was limited by the features that we defined. In our setting with no or very limited electronic record keeping it would have been challenging to incorporate for example imaging data. In settings with more extensive electronic recors this should be more feasible. Further, the ensemble learner was limited by the techniques included in its library. We included a mix of MHTM and MMTH learners, for example logistic regression and random forest. Now, the performance of our ensemble learner was already very good, but extending the list of features and techniques available to the learner would likely improve it further. Also, we used the default hyperparameter settings for each technique. Future research may improve the learner's performance by modifying the included learners' hyperparameters.

As stated above there is little research to which our study can be directly compared. We found that the ensemble learner in general reclassified events to a higher priority level and non-events to a lower priority level, compared to clinicians. This is analogous to reduced under and overtriage respectively. These concepts are used extensively in the trauma literature. Undertriage refers to for example patients with major trauma not being transferred to a trauma centre and undertriage to patients with minor trauma being transferred to a trauma centre. Three studies have used MMTH learners to limit under and overtriage of trauma patients. Talbert et al. applied a tree based learner but found no improvement over standard criteria [19]. More recent research by Follin et al. demonstrated superior performance of the tree based learner compared to a model based on logistic regression [22]. Pearl et al. used neural networks but could not demonstrate a difference [20]. Only Follin report performance measures that can be compared to our results. Their learner achieved an AUROCC of 0.82, which is substantially lower than that of our ensemble learner.

In contrast, the literature is replete with studies using MHTM learners to reduce under and overtriage, or predict trauma mortality [10, 26, 30]. The performance of these learners vary substantially, but many studies report AUROCCs that approaches that of our ensemble learner. For example, Miller et al. and Kunitake et al. achieved AUROCCs of almost 0.97 and 0.94 with their models based on logistic regression [31]. Neither of these studies however approached the problem of prioritising among trauma patients in the ED, or suggested how the models could be used to assign patients to different priority levels.

Several steps remain before a system to prioritse among adult trauma patients in the ED based on our algorithm can and should be implemented. These steps involve refining the algorithm, comparing it with other commonly used methods to prioritise patients in the ED, incorporating it into usable software, and designing an implementation study to assess both its effectiveness and safety. There are many ways in which the algorithm could be refined but we regard defining a sequence in which the variables should be measured as the most important. We think that this

sequence should be based on a combination of individual variable importance and how feasible the variables are to record. We assume that once this sequence is defined the patients with the most severe trauma could be identified very quickly using only a small subset of the variables. Further, our ensemble learner did assign more events to the green priority level than the clinicians. This should be explored in depth in future studies.

Conclusion

An ensemble machine learner developed with the SuperLearner to prioritise among adult trauma patients in the ED is non-inferior to that of clinician gestalt.

Acknowledgments

Remains to be written.

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Table 1: Sample characteristics

Characteristic	Level	Training	Test	Overall
n (%)		3415 (75.0)	1139 (25.0)	4554 (100.0)
Age in years (median [IQR])		32.0 [24.0, 46.0]	31.0 [24.0, 45.0]	32.0 [24.0, 45.0]
Sex (%)	Female	757 (22.2)	243 (21.3)	1000 (22.0)
	Male	2658 (77.8)	896 (78.7)	3554 (78.0)
Mechanism of injury (%)	Assault	516 (15.1)	169 (14.8)	685 (15.0)
	Burn	10 (0.3)	6 (0.5)	16 (0.4)
	Event of undetermined intent	4 (0.1)	0 (0.0)	4 (0.1)
	Fall	943 (27.6)	300 (26.3)	1243 (27.3)
	Intentional self harm	13 (0.4)	3 (0.3)	16 (0.4)
	Other external cause of accidental injury	492 (14.4)	164 (14.4)	656 (14.4)
	Transport accident	1437 (42.1)	497 (43.6)	1934 (42.5)
Type of injury (%)	Blunt	3379 (98.9)	1135 (99.6)	4514 (99.1)
	Penetrating	30 (0.9)	3 (0.3)	33 (0.7)
	Blunt and penetrating	6 (0.2)	1 (0.1)	7 (0.2)
Mode of transport (%)	Ambulance	1822 (53.4)	501 (44.0)	2323 (51.0)
	Police	91 (2.7)	20 (1.8)	111 (2.4)
	Private vehicle	1403 (41.1)	577 (50.7)	1980 (43.5)
	Arrived walking	99 (2.9)	41 (3.6)	140 (3.1)
Transferred (%)	No	1542 (45.2)	538 (47.2)	2080 (45.7)
	Yes	1873 (54.8)	601 (52.8)	2474 (54.3)
SBP (median [IQR])		121.0 [111.0, 132.0]	125.0 [112.0, 136.0]	122.0 [111.0, 133.0]
DBP (median [IQR])		80.0 [70.0, 87.0]	81.0 [73.0, 91.0]	80.0 [70.0, 88.8]
SpO^2 (median [IQR])		98.0 [97.0, 98.0]	98.0 [98.0, 98.0]	98.0 [97.0, 98.0]
HR (median [IQR])		86.0 [77.0, 97.0]	83.0 [77.0, 92.0]	85.0 [77.0, 96.0]
RR (median [IQR])		22.0 [19.0, 24.0]	22.0 [20.0, 24.0]	22.0 [20.0, 24.0]
EGCS (%)	1	179 (5.2)	40 (3.5)	219 (4.8)
	2	74 (2.2)	23 (2.0)	97 (2.1)
	3	119 (3.5)	29 (2.5)	148 (3.2)
	4	3013 (88.2)	1045 (91.7)	4058 (89.1)
	Non testable	30 (0.9)	2 (0.2)	32 (0.7)
VGCS (%)	1	196 (5.7)	35 (3.1)	231 (5.1)
	2	90 (2.6)	24 (2.1)	114 (2.5)
	3	42 (1.2)	19 (1.7)	61 (1.3)
	4	168 (4.9)	79 (6.9)	247 (5.4)
	5	2913 (85.3)	982 (86.2)	3895 (85.5)
	Non testable	6 (0.2)	0 (0.0)	6 (0.1)
MGCS (%)	1	67 (2.0)	10 (0.9)	77 (1.7)
	2	37 (1.1)	10 (0.9)	47 (1.0)
	3	36 (1.1)	8 (0.7)	44 (1.0)
	4	42 (1.2)	8 (0.7)	50 (1.1)
	5	186 (5.4)	63 (5.5)	249 (5.5)
	6	3043 (89.1)	1040 (91.3)	4083 (89.7)
	Non testable	4 (0.1)	0 (0.0)	4 (0.1)
AVPU (%)	Unresponsive	67 (2.0)	9 (0.8)	76 (1.7)
	Pain responsive	214 (6.3)	79 (6.9)	293 (6.4)
	Voice responsive	119 (3.5)	28 (2.5)	147 (3.2)
	Alert	3015 (88.3)	1023 (89.8)	4038 (88.7)
Delay (median [IQR])		325.0 [65.0, 1380.0]	480.0 [65.0, 1725.0]	360.0 [65.0, 1503.8]
All cause 30-day mortality (%)	No	3096 (90.7)	1049 (92.1)	4145 (91.0)
	Yes	319 (9.3)	90 (7.9)	409 (9.0)

Abbreviations and explanations: AVPU, Alert, voice, pain, unresponsive scale; DBP, Diastolic blood pressure in mmHg; Delay, Time between injury and arrival to participating centre in minutes; EGCS, Eye component of the Glasgow Coma Scale; HR, Heart rate; MGCS, Motor component of the Glasgow Coma Scale; RR, Respiratory rate in breaths per minute; SBP, Systolic blood pressure in mmHg; SpO^2, Peripheral capillary oxygen saturation; Transferred, Transferred from another health facility; VGCS, Verbal component of the Glasgow Coma Scale

Table 2: Priority levels assigned by the binned SuperLearner prediction in the training sample (n = 3415)

All cause 30-day mortality	Green (%)	Yellow (%)	Orange (%)	Red (%)	Overall (%)
No	2689 (100)	186 (97)	209 (66)	12 (6)	3096 (91)
Yes	0 (0)	6 (3)	110 (34)	203 (94)	319 (9)

Table 3: Priority levels assigned by the binned SuperLearner prediction in the test sample (n = 1139)

All cause 30-day mortality	Green (%)	Yellow (%)	Orange (%)	Red (%)	Overall (%)
No	928 (100)	62 (97)	56 (57)	3 (7)	1049 (92)
Yes	3 (0)	2 (3)	43 (43)	42 (93)	90 (8)

Table 4: Priority levels assigned by clinicians in the test sample (n = 1139)

All cause 30-day mortality	Green (%)	Yellow (%)	Orange (%)	Red (%)	Overall (%)
No	531 (100)	459 (93)	46 (58)	13 (38)	1049 (92)
Yes	1 (0)	35 (7)	33 (42)	21 (62)	90 (8)

Table 5: Priority levels assigned by SuperLearner and clinicians in complete test sample (n = 1139)

	SuperLearner						
Clinicians	Green	Yellow	Orange	Red	Rec. %	Rec. up %	Rec. down %
Green	522	2	7	1	2	2	
Yellow	370	55	59	10	89	14	75
Orange	29	6	30	14	62	18	44
Red	10	1	3	20	41		41

Reclassification (Rec.) figures refer to % of patients reclassified by the SuperLearner compared to clinicians. Rec. up and Rec. down indicates % of patients reclassified to a higher or lower priority level respectively.