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Enhancing trauma triage in low-resource settings using machine learning: a performance comparison with the Kampala Trauma Score

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Abstract

Background Traumatic injuries are a leading cause of morbidity and mortality globally, with a disproportionate impact on populations in low- and middle-income countries (LMICs). The Kampala Trauma Score (KTS) is frequently used for triage in these settings, though its predictive accuracy remains under debate. This study evaluates the effectiveness of machine learning (ML) models in predicting triage decisions and compares their performance to the KTS.

Methods Data from 4,109 trauma patients at Soroti Regional Referral Hospital, a rural hospital in Uganda, were used to train and evaluate four ML models: Logistic Regression (LR), Random Forest (RF), Gradient Boosting (GB), and Support Vector Machine (SVM). The models were assessed in regard to accuracy, precision, recall, F1-score, and AUC-ROC (Area Under the Curve of the Receiver Operating Characteristic curve). Additionally, a multinomial logistic regression model using the KTS was developed as a benchmark for the ML models.

Results All four ML models outperformed the KTS model, with the RF and GB both achieving AUC-ROC values of 0.91, compared to 0.62 (95% CI: 0.61–0.63) for the KTS ($p < 0.01$). The RF model demonstrated the highest accuracy at 0.69 (95% CI: 0.68–0.70), while the KTS-based model showed an accuracy of 0.54 (95% CI: 0.52–0.55). Sex, hours to hospital, and age were identified as the most significant predictors in both ML models.

Conclusion ML models demonstrated superior predictive capabilities over the KTS in predicting triage decisions, even when utilising a limited set of injury information about the patients. These findings suggest a promising opportunity to advance trauma care in LMICs by integrating ML into triage decision-making. By leveraging basic demographic and clinical data, these models could provide a foundation for improved resource allocation and patient outcomes, addressing the unique challenges of resource-limited settings. However, further validation is essential to ensure their reliability and integration into clinical practice.

Keywords Machine learning, Ai, Trauma, Triage systems, Emergency care

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Introduction

Injuries caused by trauma pose a major global health issue, significantly contributing to g both morbidity and mortality worldwide. Annually, approximately four and a half million deaths are attributed to traumatic injuries, accounting for nearly 8% of global mortality [1]. The burden of these injuries is disproportionately borne by low- and middle-income countries (LMICs), where 90% of all injury-related fatalities occur. This glaring inequality underscores the urgent need for effective trauma care interventions in these regions [2].

The rapid urbanisation and infrastructural development in LMICs are expected to compound the prevalence of traumatic injuries in the coming decades [3]. Despite the growing scale of this issue, trauma care in these countries faces significant challenges, including inadequate resources and a shortage of trained medical personnel. Effective management of trauma patients requires prompt diagnosis of injuries and prioritisation of resources for those in critical need, a process known as triage. Thus, there's a pressing need for models and scoring systems that can rapidly perform initial triage assessments of critically ill patients with only minimal injury data input [4].

The Kampala Trauma Score (KTS) is widely used for predicting mortality and admission in LMICs. It was originally developed for assessing traumatic injuries in resource-limited settings without advanced diagnostics [5], and has been proposed as a potential triage tool in LMICs [6–8]. The KTS is typically applied in pre-hospital settings and emergency rooms, often by clinicians and nurses and to quickly assess the severity of injuries and make immediate triage decisions. This score is advantageous for triage because it requires less information compared to other scores and is applicable to patients of all ages [9]. This score is calculated using the respiratory rate, neurological status, systolic blood pressure, patient's age, and number of serious injuries [5]. However, despite its practical advantages, research findings on its effectiveness have been varied. Some studies advocate its use as a reliable triage tool [9], while others have found it lacking in predictive strength [7].

In contrast, high-income countries commonly use advanced triage systems such as the Emergency Severity Index (ESI) to manage increasing patient loads and prioritise care for critically ill patients [10–12]. Some such tools have integrated machine learning (ML) models to enhance triage accuracy by predicting triage decisions such as hospitalisation and critical care, with studies suggesting superiority compared to traditional methods [13, 14]. Despite the well-documented potential of ML in predicting outcomes in various medical fields [15–17], its application in enhancing triage in LMICs, remains limited. Some studies have promising results, however the tools are limited to mortality or specific fields such as neurosurgery [18–20]. Furthermore, there is evidence that one size does not fit all, as models developed for high-income countries often perform poorly in LMIC settings due to different patient demographics and resource constraints [21]. This makes a compelling argument to develop ML trauma triage tools bespoke to LMIC settings.

This study aims to develop an ML-based triage system using data from a trauma registry in rural Uganda. In addition, we benchmarked the performance of these models against the KTS score. Our ML models are intended as a foundational tool to support more accurate and timely clinical decision-making. While further validation is required, these models hold promise for informing resource allocation, guiding patient management, and potentially improving outcomes in resource-limited settings.

Methods

Data description

A total of 4,109 patient records were obtained from a prospective trauma registry established at Soroti Regional Referral Hospital, Uganda, which serves a predominantly rural population. The registry was designed to capture information on trauma cases from October 2016 to July 2019, as described by Zheng et al. in their study (S1 Data) [22]. The registry form collected data on patient demographics, injury details, clinical assessments, and outcomes (S1 Appendix). The KTS [5], a well known effective score for LMICs was used to categorise injury severity, with KTS 14–16 signifying a mild injury, 11–13 a moderate injury, 10 or below a severe injury [6]. Trained clinicians and research assistants gathered data at initial patient encounters and followed up with patients until discharge or transfer.

Data preprocessing

Four relevant features from the dataset were selected to develop the ML models: age, sex, hours to hospital and mechanism of injury. The choice of features was driven by the need for algorithms in LMICs that require minimal data collection and simplicity [4], therefore basic demographics features and injury history were chosen as these should be rapid to ascertain on initial patient presentation, and this data is often be collected by hospitals as a standard matter of administration on arrival/admission. The raw data were inspected for missing values and inconsistencies, then free text values were converted to appropriate categorical data. The "sex" variable was converted to categorical data with labels "Male" and "Female". The "initial decision" (triage outcome) variable was mapped to numerical categories: 1 for "Treat and send home", 2 for "Take to theatre", 3 for "N/A(died)" and 4 for "Admit to hospital ward". Any patient data sets in which the "initial decision" value was "Send to" or "Unknown" were filtered out. The mechanism of injury was categorised into types such as blunt force, burn, fall, gunshot, and others, as indicated on the original form, and then encoded using 'one-hot encoding'. Our choice to use triage outcomes rather than mortality as the primary outcome was driven by data distribution constraints. Specifically, the 'death' variable was highly imbalanced, with only 63 cases labelled as '1' (died) compared to 3946 labelled as '0' (survived). This severe imbalance would limit the reliability and predictive performance of machine learning models aimed at mortality prediction, as the model would be biased toward the majority class, potentially leading to high false-negative rates.

Development of machine learning models

Four ML models were trained and evaluated including Logistic Regression (LR), Random Forest (RF) Classifier, Gradient Boosting (GB) Classifier and Support Vector Machines (SVM). The dataset was split into training (70%) and testing (30%) sets. A pipeline was created for each model in order to transform the raw data into trained and deployable ML models, incorporating the preprocessing steps and the classifier. Each pipeline was trained on the training set and evaluated on the testing set.

A hyperparameter tuning process was conducted to determine the best parameters for each model. For the LR, a regularization parameter of 10 was selected. The SVM model was configured with a regularisation parameter of 100.0, an 'rbf' kernel, degree of 2, and gamma set to 'scale'. The RF model was tuned with bootstrap set to True, a maximum depth of 10, a minimum of 1 sample per leaf, a minimum of 2 samples per split, and 500 estimators. For the GB model, the hyperparameters included a maximum depth of 3, a minimum of 2 samples per leaf, a minimum of 10 samples per split, 50 estimators, and a learning rate of 0.1.

The performance of each model was evaluated using accuracy, precision, recall, f1-Score and area under the receiver operating characteristic curve (AUC-ROC). The AUC-ROC provides a measure of the overall ability of the model to distinguish between classes, with values closer to 1 indicating better performance. It relates to the traditional sensitivity and specificity metrics by reflecting the trade-off between true positive rates and false positive rates across different threshold settings. ROC curves were plotted for each model to visualise their performance. To provide insights into the most influential factors in the prediction process, feature importances for the best performing model were calculated. To ensure reliability of model performance, a stratified 5-fold cross-validation was performed and accuracy scores were calculated for each fold and iteration, and the mean and 95% confidence interval of the cross-validation accuracy were computed.

Statistical analysis

We analysed the relationship between the KTS and the initial clinical decision to examine if KTS significantly influences clinical decisions. We performed a chi-squared test to assess the association between KTS categories and initial decision categories.

We then built a multinomial logistic regression model using KTS to predict the initial clinical decision. The model is represented by:

$$P\left(y_i = j\right) = \frac{e^{\beta_{0j} + \beta_{1j} \cdot \text{kts}}}{\sum_{k=0}^{J} e^{\beta_{0k} + \beta_{1k} \cdot \text{kts}}}$$

where β_{0j} is the intercept for outcome j and β_{1j} is the coefficient for the predictor KTS.

A stratified 5-fold cross-validation was performed. Accuracy scores were calculated for each fold during each iteration, and the mean and 95% confidence interval of the cross-validation accuracy were subsequently computed. This model was used to benchmark our ML models. To compare our ML models with the KTS-based model, we calculated performance metrics for the KTS-based model and ran paired t-tests to statistically compare it with the best-performing ML model.

The descriptive statistics for the patient demographics, injury details, and outcomes were done in R v4.2.1 using ggplot2 v3.5.0 [23], readxl v1.4.3 [24], dplyr v1.1.4 [25], tidyr v1.3.1 [26], ggsci v3.2.0 [27] and kableExtra v1.4.0 [28]. The data manipulation, ML model development, statistical modelling, and scientific computing were performed using Pandas v2.1.3 [29], Scikit-learn v1.3.2 [30], Statsmodels v0.14.0 [31] and Scipy v1.11.3 [32] respectively, in Python v3.9. We followed the TRIPOD + AI guidance on transparent reporting of clinical prediction models that use ML, and the checklist has been provided as part of supplementary material (S1 Checklist) [33].

Results

Sex and age distribution

The dataset comprised a total of 4,109 patients. The majority of the patients were male (62%), followed by females (37%), and a small proportion (1%) had missing values for sex. The most represented age groups represented in the dataset were 0–9 years (25%), 20–29 years (20%), and 10–19 years (18%) were the most (Table 1).

Mechanism of injury by age group

Road traffic accidents were the predominant cause of injury across most age groups. For example, in the age group 20–29 years, road traffic accidents accounted for

Table 1 Sex and age distribution of patients

Characteristic	Category	Count	Percentage (%)
Demographics	Sex		
	Male	2560	62.30
	Female	1528	37.19
	NA	21	0.51
	Total	4109	100
	Age Group		
	0–9	1028	25.02
	10–19	734	17.86
	20–29	824	20.05
	30–39	573	13.94
	40–49	327	7.96
	50–59	216	5.26
	60–69	158	3.85
	70–79	122	2.97
	80–89	74	1.80
	90–99	14	0.34
	100–109	2	0.05
	NA	37	0.90
	Total	4109	100
Initial Decision	Treat and send home	1673	40.72
	Take to theatre	1501	36.53
	N/A (Died)	803	19.54
	Admit to hospital ward	32	0.78
	NA	100	2.43
	Total	4109	100
Mechanism of Injury	Animal Bite	114	2.77
	Blunt Force	698	16.99
	Burn	116	2.82
	Fall	1463	35.61
	Gunshot	11	0.27
	Other	73	1.78
	Poisoning	36	0.88
	Road Traffic Accident	1432	34.85
	Stab/Cut	156	3.80
	NA	10	0.24
	Total	4109	100
Hours to Hospital	Less than 1 h	778	18.93
	1 to 6 h	1103	26.84
	Over 6 h	1973	48.02
	NA	255	6.21
	Total	4109	100

50% of the injuries. Falls and blunt forces were also significant contributors, with falls representing 59% in the 50–59 years age group and blunt forces accounting for 26% in the 30–39 years age group. This distribution highlights the variation in injury mechanisms based on age (Fig. 1).

Mechanism of injury by sex and initial decision

Males were more frequently involved in road traffic accidents (38%), which often required theatre intervention (69%). Females showed a relatively higher proportion of fall injuries (40%) and road traffic accidents (30%), with most falls leading to treatment and being sent home (51%) and deaths from the road traffic accidents (64%) (Fig. 2). The majority of trauma patients requiring surgery were male.

KTS and admission decision

The relationship between the KTS and the initial clinical decision was analysed using a chi-squared test. The results indicated a highly significant relationship between the KTS and the initial clinical decision (χ^2 = 243.66,

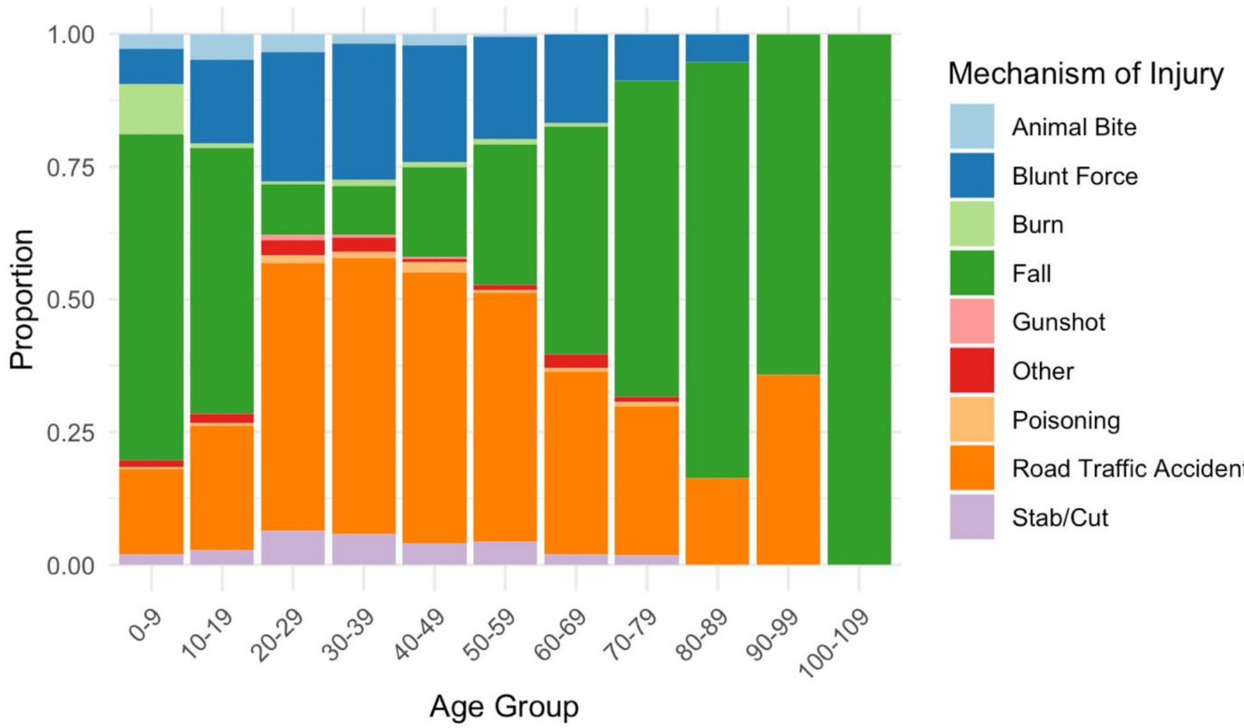

Fig. 1 Injury mechanisms by age group

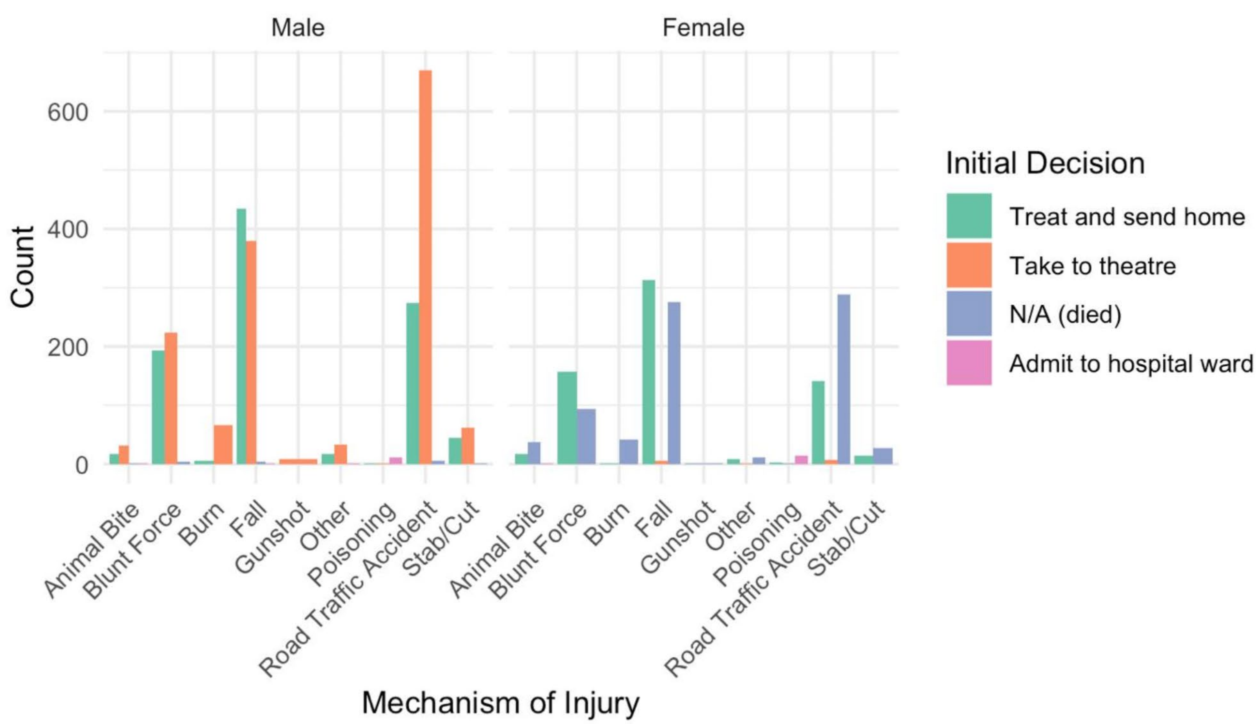

Fig. 2 Mechanism of injury by sex and initial decision

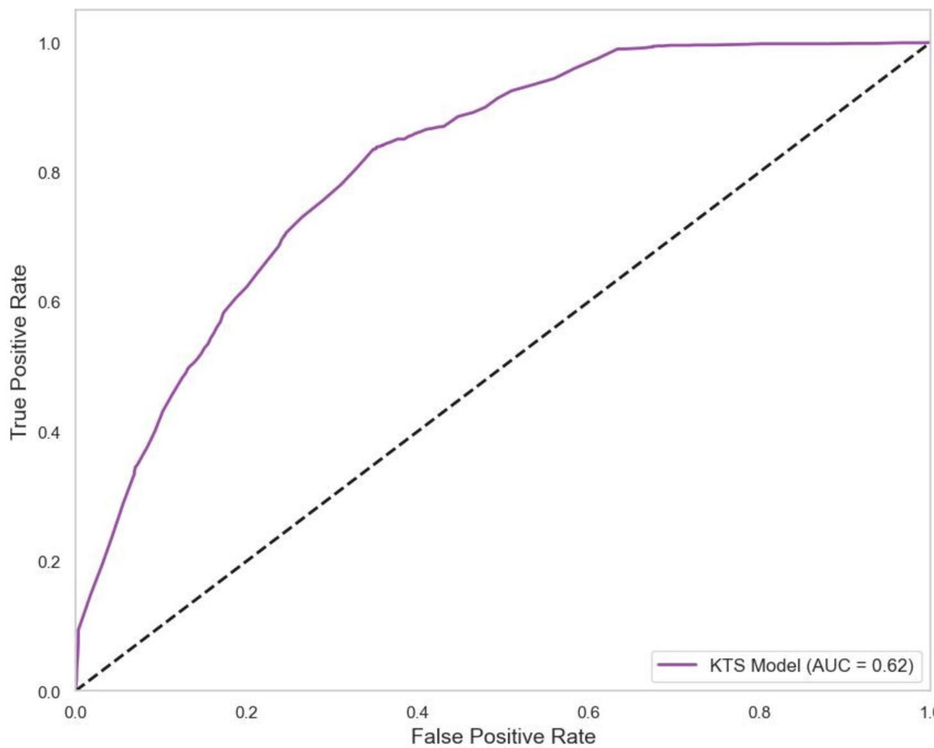

Fig. 3 ROC curve for the KTS-based multinomial logistic regression model

Table 2 Performance metrics for various classifiers including LR, RF, GB, SVM, and the KTS model. Note: CV stands for cross-validation

Classifier	Accuracy	Precision	Recall	F1-Score	AUC-ROC	CV Mean Accuracy (95% CI)	CV Mean AUC-ROC (95% CI)
LR	0.63	0.63	0.63	0.63	0.89	0.63(0.62, 0.63)	0.79(0.79,0.80)
RF	**0.69**	0.69	0.69	0.68	**0.91**	0.68(0.67,0.68)	0.82(0.82,0.82)
GB	0.68	0.68	0.68	0.68	**0.91**	0.67(0.67,0.68)	0.83(0.83,0.83)
SVM	0.69	0.69	0.69	0.68	0.90	0.67(0.67,0.67)	0.80(0.80,0.80)
KTS	0.54	0.42	0.54	0.45	0.62	0.54(0.52,0.55)	0.61(0.61,0.63)

$p < 0.001$), suggesting that KTS is a relevant factor in determining the initial management of trauma patients. Subsequently, a KTS-based Multinomial Logistic Regression model was fitted to predict the initial clinical decision (Fig. 3). The model yielded an AUC-ROC of 0.62 (95% CI 0.61–0.63), indicating moderate discriminative ability.

To investigate the role of predictor variables in triage decision-making, we analysed distributions of age, transport time to hospital, sex, injury mechanism, and KTS score across triage outcomes (Supplementary Tables S1–S5). Patients admitted or requiring surgery tended to be older on average, while younger patients were more likely to be treated and discharged ($p < 0.001$). Prolonged prehospital transport times correlated significantly with more severe outcomes ($p < 0.001$), underscoring the impact of delayed care. Sex distribution also varied markedly by triage outcome ($p < 0.001$), with males overrepresented in critical cases. Injury mechanisms showed distinct patterns, with road traffic accidents significantly represented in severe cases ($p < 0.001$), suggesting its potential as a high-risk indicator. KTS scores aligned predictably, with lower scores associated with more intensive interventions ($p < 0.001$).

Machine learning model performance

We evaluated four ML models: LR, RF, GB, and SVM (Table 2). Additionally, we compared them with the KTS model. The highest performing ML model (RF) significantly outperformed the KTS-based model in predicting the initial clinical decision ($p = 0.005$). The RF and GB classifiers demonstrated the highest AUC-ROC values of 0.91, indicating excellent model performance in distinguishing between different classes. The SVM classifier also showed high AUC-ROC (0.90), closely followed by LR (0.89). The KTS-based model exhibited a significantly lower AUC-ROC of 0.62, reflecting its relatively poorer performance. The RF model achieved the highest accuracy of 0.69, with a 95% confidence interval (CI) of 0.68 to 0.70, indicating a reliable performance. GB and SVM followed closely with accuracies of 0.68 and 0.69, respectively. The KTS-based model had the lowest accuracy at 0.54 (95% CI: 0.52–0.55). The mean accuracy from cross-validation (CV) for the ML models ranged from 0.63 to 0.68, with RF and GB showing the highest mean CV accuracies.

The RF and GB models exhibited similar and superior performance with AUC values of 0.91. The SVM and LR models followed closely behind with AUC values of 0.90 and 0.89, respectively. The KTS model had the lowest AUC of 0.62, demonstrating its lower discriminative capability compared to the ML models. The ROC curves reaffirm the superior performance of the ML models over the KTS-based model in predicting the initial clinical decisions, as evidenced by their higher AUC values (Fig. 4).

Feature importance analysis

The feature importance for the highest-performing models, GB and RF, was analysed to provide insights into the most influential factors in the prediction process. The figure below presents the feature importance for these models (Fig. 5).

The GB model identified 'sex', 'hours to hospital,' and 'age' as the most important features. The mechanisms of injury such as 'burn,' 'fall,' and 'road traffic accident' also played significant roles in the prediction process. Similarly, the RF model highlighted 'sex', 'hours to hospital,' and 'age' as the key features. The model also found that the mechanisms of injury including 'fall,' 'poisoning,' and 'burn' were important for predicting the initial clinical decision.

Discussion

This study aimed to develop and evaluate an ML-based triage tool using data from a trauma registry in rural Uganda, benchmarking its performance against an established tool in such settings, the KTS. Our findings indicate that ML models demonstrate superior performance compared to the KTS in predicting triage decisions. The predictive performance of the developed ML models is similar to those observed in other ML-based studies in high income countries [10, 34, 35].

The KTS score, developed for resource-limited settings, has been proposed as a practical triage tool due to its simplicity and applicability across all age groups [5, 36]. Despite being highly correlated with admission outcomes ($p < 0.01$), the KTS-based model achieved an AUC-ROC value of 0.61 (95% CI 0.61–0.63) in predicting the triage decision. The low discriminative ability of the KTS in the current study is consistent with findings from a study that applied KTS to a cohort of 15,617 patients in Malawi (AUC-ROC 0.62), to predict admission [7]. This study found that KTS was not a strong predictor of prolonged

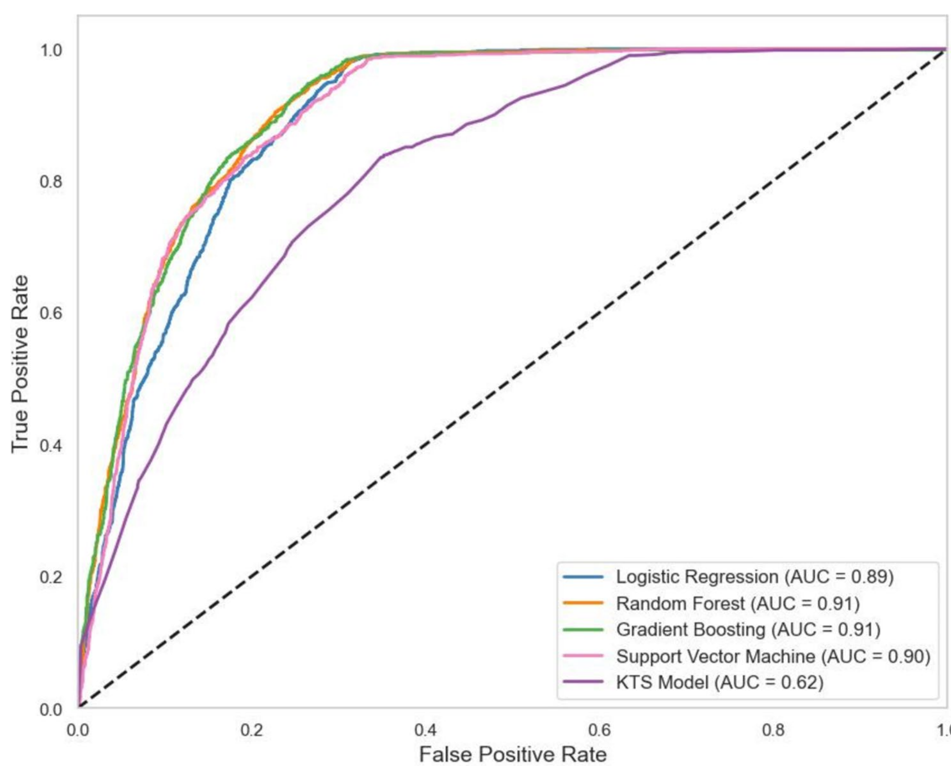

Fig. 4 Illustration of the ROC curves for the evaluated models, showing the trade-off between sensitivity (True Positive Rate) and specificity (False Positive Rate)

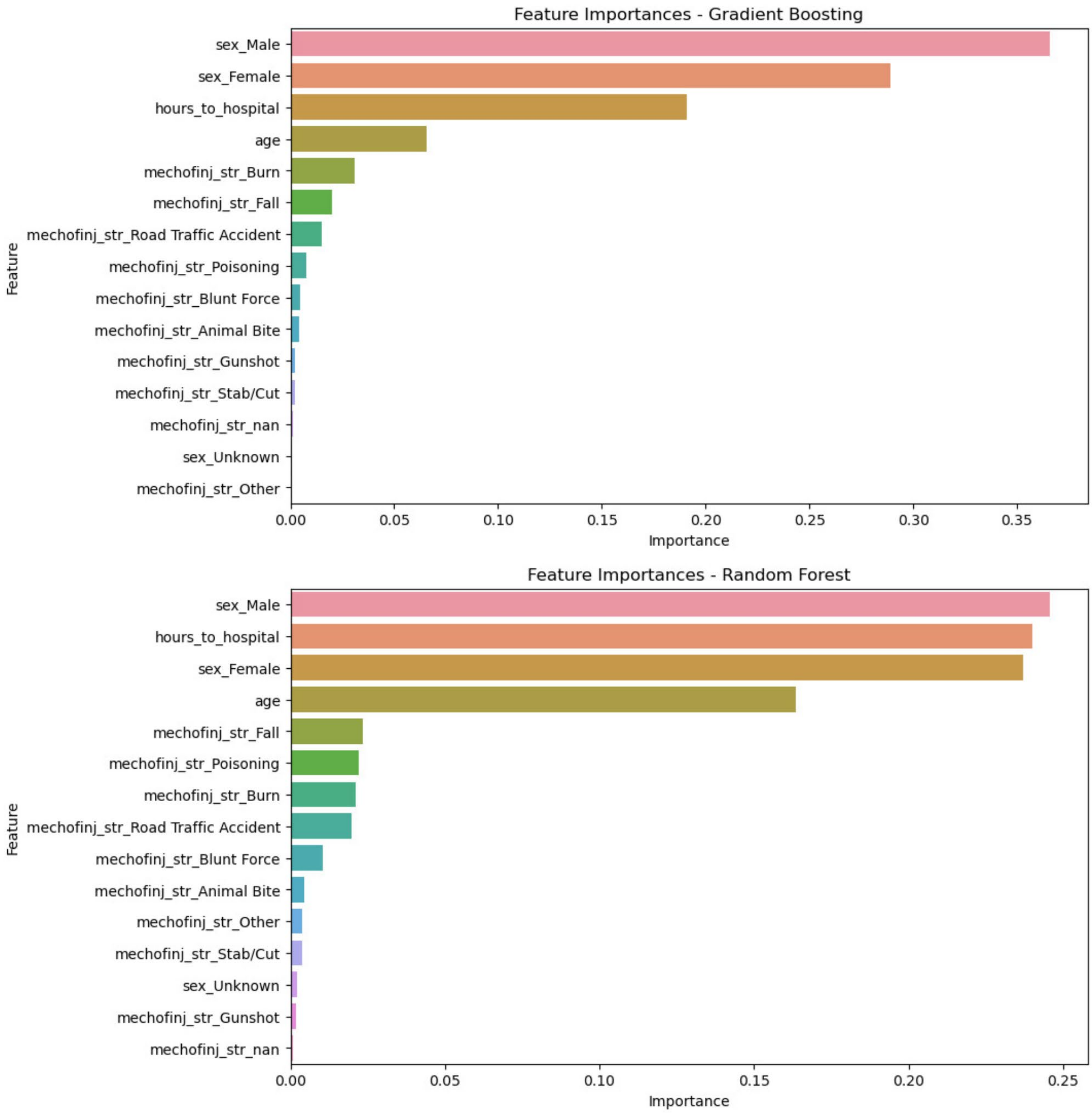

Fig. 5 Illustration of the most important features for the GB and RF models

hospital stays, highlighting its limitations as a standalone triage tool.

In comparison, however, ML models, particularly ensemble models (RF and GB classifiers), were found to perform superiorly in predicting triage decision. During model development we prioritised model interpretability and practicality by using fewer variables (sex, age, hours between the accident and admission and the mechanism of injury), ensuring that the models remain easy to implement in clinical settings. Collecting extensive data, such as respiratory rate, neurological status, systolic blood pressure, and laboratory results, can be challenging and costly in LMICs. Therefore, we aimed to build a model that could effectively triage patients upon arrival with minimal but essential information. Variables like type of injury, hours to hospital, age, and sex are straightforward to collect and provide a solid foundation for accurate triage.

Our findings are consistent with those of a study conducted by De Hond et al. in the Netherlands, which compared ML models for predicting hospital admissions at different time points (triage, 30 min, and 2 h after

ED registration) [14]. Similar to our results, their study found that ML models, particularly GB, performed well across all time points without significant performance improvement when additional information, such as laboratory results, was included. This reinforces the potential of ML models to deliver reliable predictions even with limited data. However, to our knowledge, no previous studies have developed ML models to guide triage decision making at trauma wards in sub-Saharan Africa and other LMIC settings. Possible bottlenecks to this development could be the shortage of locally relevant datasets for model development, therefore the establishment of trauma registries such as that at Soroti Regional Referral Hospital are essential.

The feature importance analysis revealed that sex, hours to hospital, and age were the most significant predictors of trauma outcomes in both the GB and RF models. This aligns with clinical expectations and underscores the critical role of these variables in determining patient prognosis. Notably, the inclusion of 'hours to hospital' as a predictor highlights the impact of delays in receiving medical care. Prolonged prehospital time is well known to be associated with worse clinical outcomes [37], a reality often exacerbated by infrastructural and resource challenges in LMICs. Current scores like KTS do not account for prehospital time, which is a crucial factor in trauma care, especially in resource-limited settings [38–40].

In line with previous literature, age was found to be an important factor in triaging trauma patients. Advanced age is associated with worse outcomes following injury, owing to decline in physiological response to injury, reduced physiological reserve, and more numerous comorbidities [41]. Therefore, the inclusion of age in triaging tools has been previously emphasised, and its relevance is reflected by its importance in the current study. Our findings showed that sex, was a significant predictor to the predictive performance of the models. This finding aligns with the broader literature, which consistently shows a higher incidence of trauma among males, especially in LMICs [22, 42, 43]. The overrepresentation of males in trauma cases is often attributed to their involvement in high-risk occupations and activities, which carry greater exposure to injury [22]. These patterns underscore the importance of including sex in triage models, as it enhances the prediction of outcomes.

The improved predictive performance of ML models compared to KTS in our study suggests the potential value of incorporating data-driven approaches into trauma triage decision-making in LMICs. However, as these findings are based on retrospective data from a single centre, further validation across multiple settings and prospective evaluation of clinical impact will be essential before recommending any systematic changes to existing triage protocols. By leveraging basic demographic and clinical information, ML models have potential to provide timely and accurate triage decisions, reducing triage waiting times, optimising resource allocation, reducing costs, and improving patient outcomes [13, 44, 45]. This is particularly crucial in settings where advanced diagnostic tools are scarce, and rapid decision-making is essential. Integrating ML models into clinical practice could enhance decision-making processes, support clinicians with real-time predictions, reduce the burden on overworked medical personnel, and ultimately improve patient outcomes.

Limitations

While our study highlights the potential of ML models in trauma triage, it is essential to acknowledge its limitations. First, the performance of ML models is highly dependent on the quality and completeness of the data used for training the models. In the current study, data had some degree of incompleteness, posing a significant challenge in model development. Second, the study focused on a limited set of predictors that were readily available in the datasets. While this approach was intentional to enhance the model's practicality and applicability in resource-limited settings, it may have excluded other potentially important variables that could improve the model's predictive performance.

Third, fairness methods were not specifically applied in this preliminary model, which focused on establishing a foundational approach. We recognise potential biases in the data, such as the higher incidence of fall injuries among female patients, which may reflect variations in injury reporting or severity. Future work should include fairness assessments, examining model performance across demographic subgroups to ensure equitable and unbiased triage recommendations. Lastly, while ML models offer promising improvements over traditional scoring systems like KTS, the interpretability of these models remains a challenge. In clinical practice, the ability to understand and trust model predictions is essential for adoption. Efforts to enhance model transparency and provide clear explanations of predictions will be necessary to facilitate integration into clinical workflows.

Conclusion

The findings from our study, together with insights from existing research, highlight the potential of ML models to enhance trauma care in LMICs. The next step involves advancing these models into accessible platforms for real-time clinical use as complementary tools alongside existing triage systems, potentially through simplified scoring systems via mobile applications. While preliminary results are promising, further work is needed to address data quality issues, improve model interpretability, and ensure clinical acceptability. Critical to this advancement is the development of robust trauma registries across sub-Saharan Africa, which will enable not only ML model development but also systematic improvements in clinical care, surveillance and quality assurance. By providing timely and accurate predictions, these models could significantly improve triage efficiency and resource allocation, with the ultimate goal of improving patient outcomes. With careful development and rigorous validation, ML models could form a valuable foundation for advancing trauma care in resource-limited environments.

Abbreviations

KTS	Kampala trauma score
ML	Machine learning
LR	Logistic regression
RF	Random forest
GB	Gradient boosting
SVM	Support vector machine
AUC-ROC	Area under the curve of the receiver operating characteristic curve
LMICs	Low- and middle-income countries
ESI	Emergency severity index
CV	Cross-validation

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12873-025-01175-2.

Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

Supplementary Material 4

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Author contributions

MN: Conception, Data analysis, Data Interpretation, Writing-Original draft; TMK: Data Interpretation, Writing-Final draft; HP: Data Interpretation, Writing-Final draft; KS: Data Interpretation, Writing-Final draft; SMN: Conception, Data Interpretation, Writing-Final draft. All authors read and approved the final manuscript.

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Data availability

The data and source code for the data preparation and model training is provided on the GitHub page: https://github.com/mikensubuga/ml-trauma-triage.

Declarations

Ethics approval and consent to participate

The data used in the study was originally collected and reported by Zheng et al.(2021). The original study was conducted following ethical approval obtained from the Mulago National Referral Hospital Research Committee, the Uganda National Council of Science and Technology, and the Institutional Review Board of the University of California, San Francisco. Written consent could not be feasibly obtained for all study patients due to the acuity of their medical injuries; however, oral informed consent was granted by all adult patients during their hospital encounter, with permission from parents/guardians obtained for all patients under 18 years of age and documented in the registry. As this study involved the secondary analysis of this already published and anonymised data, no further ethics approval or consent was necessary. The data were accessed for research purposes on 24 Oct 2023, and the authors did not have access to any information that could identify individual participants during or after data collection.

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Competing interests

The authors declare no competing interests.

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