Pediatric Surgery International (2024) 40:20
https://doi.org/10.1007/s00383-023-05602-y

ORIGINAL ARTICLE

A simple machine learning approach for preoperative diagnosis of esophageal burns after caustic substance ingestion in children

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Accepted: 16 November 2023
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Abstract

Purpose The unresolved debate about the management of corrosive ingestion is a major problem both for the patients and healthcare systems. This study aims to demonstrate the presence and the severity of the esophageal burn after caustic substance ingestion can be predicted with complete blood count parameters.

Methods A multicenter, national, retrospective cohort study was performed on all caustic substance cases between 2000 and 2018. The classification learner toolbox of MATLAB version R2021a was used for the classification problem. Machine learning algorithms were used to forecast caustic burn.

Results Among 1839 patients, 142 patients (7.7%) had burns. The type of the caustic and the PDW (platelet distribution width) values were the most important predictors. In the acid group, the AUC (area under curve) value was 84% while it was 70% in the alkaline group. The external validation had 85.17% accuracy in the acidic group and 91.66% in the alkaline group.

Conclusions Artificial intelligence systems have a high potential to be used in the prediction of caustic burns in pediatric age groups.

Keywords Caustic substance ingestion · Machine learning · Artificial intelligence · Children

Introduction

There is an unresolved debate about the management of corrosive ingestion which is a major problem both for the patients and healthcare systems. Per the wide availability of caustic substances in cleaning agents, its prevalence is around 1 to 5 in 1000 patient admissions per year with an annual mortality rate of around 4–10% [1, 2]. Moreover, the risk for stricture formation and long-term gastrointestinal morbidity is 7–25%. It is especially a significant problem in developing countries where the numbers are probably underestimated due to ineffective reporting systems. The management of caustic substance ingestion varies widely. The common approach is an endoscopic evaluation within 24–48 h after ingestion even though others recommend earlier intervention [3–6]. Moreover, with the improvements in the safety measurements and the high number of false negative results with endoscopy, some authors recommend that the endoscopy is unnecessary under pre-determined criteria [5, 7, 8].

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Published online: 13 December 2023

However, patients admitted to the hospitals with suspicion of caustic ingestion are being routinely evaluated with certain diagnostic procedures, one of which is the complete blood count (CBC). The parameters involved in CBC have been tremendously investigated for any correlation with the inflammatory response of the body [9–12]. The main limitation of these studies is the limited number of patients and the use of classical statistical techniques. On the other hand, multivariate decision criteria can be created in medical investigations using a variety of machine learning (ML) methods and techniques. Simple conceptual decision-making models with learnability are frequently employed for diagnosis and classification purposes [13–16].

The inconsistency between the symptoms and the severity of the injury is one of the biggest challenges in this patient group [17]. In the emergency center, it is difficult for clinicians to have a prompt prediction of the current condition of the patient per the miscellaneous characteristics of the products ingested. Regardless of the current guidelines, the lack of a consensus on the management of these patients necessitates a reliable, easy, quick, and repeatable tool to diagnose the presence and severity of burns after suspected caustic ingestion. Hence, the main hypothesis of this study is that the presence and the severity of the esophageal burn after caustic substance ingestion can be predicted with complete blood count parameters.

Methods

Data acquisition

In this multicenter, national, retrospective cohort analysis, data were obtained from hospital electronic medical records after Institutional Review Board approval (2019.012. IRB2.001). The cases of all patients under the age of 18 who were admitted between 2000 and 2018 with suspicion of ingesting a caustic chemical were included. STROBE criteria were adhered to in this study [18]. Data were collected by patients' healthcare providers who also oversaw patient recruitment, data completeness, and accuracy.

Dataset

The deployed system collects information on demographics, patient history, CBC results, and outcomes. There were a total of 1999 observations, 19 variables, and the patient's overall diagnosis. Based on the Zargar classification, the patient's clinical diagnoses were made (Table 1) [19]. Since the data were acquired from various hospital's databases, some values may have been missing as a result of technical and medical issues, or staff decisions. These observations were excluded from the dataset, resulting in 1839 observations in total. The dataset was grouped into two as Control in which the patients did not have gastrointestinal caustic burn or had Grade 1 caustic burn, and Burn in which the patients had Grade 2 or 3 caustic burn in the gastrointestinal system. For external validation, a total of 3514 healthy subjects who had CBC for other reasons were included in the study. Since all data of healthy people belong to the Control group, the new results (accuracy and the number of true positives) were compared by the previously obtained values of specificity and balanced accuracy.

Table 1 Zargar classification for caustic substance ingestion

	Description
Grade 0	Normal mucosa
Grade 1	Edema and erythema of the mucosa
Grade 2	
A	Hemorrhage, erosions, blisters, superficial ulcers
B	Circumferential lesions
Grade 3	
A	Focal deep gray or brownish–black ulcers
B	Extensive deep gray or brownish–black ulcers
Grade 4	Perforation

The effective operation of ML algorithms depends on data preprocessing. In order to apply ML methods, the missing data were filled with the average of the relevant variable after the data for both groups were pooled.

Machine learning algorithm

The classification learner toolbox of MATLAB version R2021a was used for the classification problem. First, a ten-fold cross-validation procedure was applied to the data set. Then, three types of ML algorithms, namely decision tree (DT) algorithms, tree-based ensemble (TBE) algorithms, and support vector machine (SVM) algorithms were used to forecast caustic burn. Since the data is quite unbalanced concerning group sizes, balanced accuracy was used instead of accuracy. Apart from this measure, specificity, sensitivity, and area under the curve (AUC) are given for each classifier and both imputation techniques. Due to unbalanced data, the obtained sensitivity values were remarkably smaller than the specificity values. In order to overcome such imbalanced classification problems, a cost-sensitive learning approach (CSLA) was used.

Statistical analysis

MATLAB version R2021a and IBM SPSS Statistics 26.0.0 (Chicago, IL) were used to conduct the statistical analysis. Descriptive statistics were used to summarize the

characteristics of the study sample, with continuous data reported as means with standard deviations and dichotomous data provided as percentages. The chi-square test and z-test were applied to the dichotomous data to examine the relationship between the variables and the statistically significant variations in the proportions. The Kolmogorov–Smirnov test was used to determine the normality of the distribution of continuous data. As a result, the Mann–Whitney *U* test was used for nonparametric variables and the student's *t*-test for parametric variables to examine statistically significant differences between groups. If the p-value was 0.05, statistical differences were deemed significant.

Results

There were 1839 patients included in the study, 1066 (57,97%) of which were male. The mean age was 3.13 ± 3.05 years. Although there was a predilection in the male population, the chi-square test of independence showed no statistically significant relationship between gender and the patient's diagnostic result ($p = 0.74$). The average time to be admitted to the hospital was 1.16 ± 0.48 days. Among all, 85.92% (1580) of the patients had acidic substances ingested. There were 1387 (75.42%) patients who had no burns, 310 (16.86%) patients had grade 1 burn, 140 (7.61%) patients had grade 2 burn, and 2 (0.11%) patients had grade 3 burn.

The Control group had 1697 (7.72%) patients and the Burn group had 142 patients as stated in Table 1. The groups were similar per gender and age characteristics. The acidic substances had a higher ratio in the Burn group when compared to the Control group which had a statistically significant difference. The analysis of the complete blood count did not reach statistical significance in any parameter except lymphocyte count.

The results obtained from optimizable classifiers for each algorithm were given in Table 2. The balanced accuracy increased for each classifier when the imputation process was applied to both groups individually. The highest balanced accuracy values, 70.83%, were obtained when DT Classifier and TBE Classifier classifiers were used. The type of ingested substance and the PDW values were the most important predictors in forecasting the presence of a burn.

Table 3 presents the CSLA approach. As expected, the specificity values decreased to a certain extent, while sensitivity values remarkably increased. Consequently, the balanced accuracy increased for each ML classifier and both imputation techniques. When the imputation process was applied to the pooled data, all ML classifiers yielded the same results. For the imputation technique that handles both groups individually, the DT classifier produced the highest balanced accuracy value, namely 79.53%. The type of the caustic and the PDW values were the most important predictors.

Since one of the parameters that caused unbalance in the dataset was the type of the substance, the dataset was

Table 2 Comparison of the group characteristics

	Burn group ($n = 142$)	Control group ($n = 1697$)	p
Age (years)	3.45 ± 3.60	3.10 ± 3.00	0.359
Gender (male)	88 (62.0%)	978(57.6%)	0.314
Complaint time (days)	1.08 ± 0.33	1.17 ± 0.49	0.056
Type substance (acid)	88 (62.0%)	171 (10.1%)	**0.000**
WBC	11,223.38 ± 4335.94	11,049.05 ± 3502.04	0.660
HGB	11.78 ± 1.19	11.85 ± 1.13	0.231
HTC	35.32 ± 3.52	35.98 ± 3.23	0.233
RDW	14.67 ± 2.15	14.43 ± 1.79	0.256
MCV	73.89 ± 6.07	74.91 ± 6.04	0.065
MCHC	33.24 ± 2.18	33.44 ± 1.61	0.727
MPV	8.82 ± 1.24	8.83 ± 1.17	0.896
PLT	337,065.96 ± 90,210.30	334,776.00 ± 92,409.16	0.812
PDW	12.00 ± 3.04	12.38 ± 3.05	0.119
LYMP	5025.88 ± 2277.23	5369.28 ± 2310.86	**0.047**
NEUT	4847.83 ± 3218.87	4443.47 ± 2699.27	0.351
NEUT/LYMP	1.26 ± 1.27	1.11 ± 1.41	0.086

Values are expressed as means ± standard deviations or counts (percentage of the group). *p*-values are reported in bold for significant differences at significance level $\alpha < 0.05$

WBC White blood cell, *HGB* Hemoglobin, *HTC* Hematocrit, *RDW* Red cell distribution width, *MCV* Mean corpuscular volume, *MCHC* Mean corpuscular hemoglobin concentration, *MPV* mean platelet volume, *PLT* Platelet, *PDW* Platelet distribution width, *LYMP* Lymphocyte, *NEUT* Neutrophile

Table 3 Ten-fold cross-validation results obtained from different ML classifiers

	Specificity (%)	Sensitivity (%)	Balanced accuracy (%)	AUC
DT	98.00–98.00	31.69–43.66	64.84–70.83	0.73–0.73
TBE	99.65–98.00	14.08–43.66	56.87–70.83	0.81–0.73
SVM	97.29–97.53	34.51–36.62	65.90–67.07	0.71–0.73

The first results were obtained for the imputation process that uses the pooled data. On the other hand, the second results were obtained when the imputation process was applied to both groups individually

ML Machine learning, *AUC* Area under curve, *DT* Decision tree classifier, *TBE* Tree-based ensemble classifier, *SVM* Support vector machine classifier

Table 4 Ten-fold cross-validation results obtained from different ML classifiers using CSLA

	Specificity (%)	Sensitivity (%)	Balanced accuracy (%)	AUC
DT	92.65–92.16	61.97–66.90	77.31–79.53	0.72–0.77
TBE	92.65–91.63	61.97–64.79	77.31–78.21	0.72–0.77
SVM	92.65–89.98	61.97–61.97	77.31–75.98	0.72–0.81

The first results were obtained for the imputation process that uses the pooled data. On the other hand, the second results were obtained when the imputation process was applied to both groups individually

ML Machine learning, *AUC* Area under curve, *DT* Decision tree classifier, *TBE* Tree-based ensemble classifier, *SVM* Support vector machine classifier, *CSLA* Cost-sensitive learning approach

divided into two acidic and alkaline. The complaint time, HGB, RDW, MCV, MPV, and PDW in the acidic group were the parameters that had statistically significant differences while the basic group had no difference in any parameter. In the acid group the highest AUC value, namely 0.84, was obtained when the TBE classifier was used for the data in which the imputation process was applied to both groups individually (Table 4). When DT with CSLA was used for the data in which the imputation process was applied to both groups individually, the best-balanced accuracy (80.82) was achieved. In the alkaline group, the balanced accuracy to detect the corrosive group was about 70% for DT and TBE, which were more successful than SVM. PDW is the most important predictor in each group. In the acidic group, it was followed by WBC and MPV while in the alkaline group, RDW was the second most important predictor.

The healthy subjects were selected on purpose since, in many scenarios, parents are not sure if the child ingested them or not. The type of the substance was selected as acid and alkaline, respectively. Since the type of caustic substance ingested is extremely important, it resulted in deceptive and conflicting results as seen in Table 5.

Similar tests were also applied for the models trained by the data composed of only acidic and alkaline substances alone. The previous results that were obtained for different classifiers and both imputation techniques and the corresponding test results are compared in Tables 6 and 7. As seen from the table, the accuracies of the tests are between 85.17 and 91.66% and they are higher than previously obtained specificity values for each scenario.

Discussion

Caustic substance ingestion is still a problem in developing countries. It affects mostly children under the age of six when there is a high tendency to put objects into their mouths. Although foreign body ingestion in Turkey is mostly seen in females, the incidence of caustic substance ingestion is higher in the male group [5, 9, 20]. Regardless of the cause, accidental, or purpose, it also has the potential to cause serious injury in the gastrointestinal system with

Table 5 Ten-fold cross-validation results obtained from different ML classifiers for the data including acidic and alkaline corrosive substance

		Specificity (%)	Sensitivity (%)	Balanced accuracy (%)	AUC
Acid	DT	83.63–80.12	48.86–70.45	66.24–75.29	0.65–0.70
	TBE	88.30–74.27	45.45–84.09	66.88–79.18	0.70–0.84
	SVM	76.02–74.85	57.95–57.95	66.99–66.40	0.72–0.72
	DT with CSLA	80.12–69.59	55.68–92.05	67.90–80.82	0.72–0.82
	TBE with CSLA	70.76–68.42	69.32–89.77	70.04–79.10	0.71–0.81
	SVM with CSLA	69.01–69.59	70.45–68.18	69.73–68.89	0.74–0.74
Alkaline	DT with CSLA	56.00–56.50	85.19–83.33	70.59–69.92	0.71–0.64
	TBE with CSLA	56.00–61.00	85.19–81.48	70.59 – 71.24	0.71–0.71
	SVM with CSLA	76.00–76.50	55.56–61.11	65.78–68.81	0.71–0.72

The first results were obtained for the imputation process that uses the pooled data. On the other hand, the second results were obtained when the imputation process was applied to both groups individually

ML Machine learning, *AUC* Area under curve, *DT* Decision tree classifier, *TBE* Tree-based ensemble classifier, *SVM* Support vector machine classifier, *CSLA* Cost-sensitive learning approach

Table 6 The comparison of the results of whole trained data and external validation

		Trained data		External validation	
		Specificity (%)	Balanced accuracy (%)	Accuracy %	True positive
Acid	DT	98.00–98.00	64.84–70.83	88.67–88.65	3116–3115
	TBE	99.65–98.00	56.87–70.83	95.90–88.65	3370–3115
	SVM	97.29–97.53	65.90–67.07	88.84–89.10	3122–3131
	DT with CSLA	92.65–92.16	77.31–79.53	0.00–0.23	0–8
	TBE with CSLA	92.65–91.63	77.31–78.21	0.00–81.47	0–2863
	SVM with CSLA	92.65–89.98	77.31–75.98	0.00–0.51	0–18
Alkaline	DT	98.00–98.00	64.84–70.83	100.00–100.00	3514–3514
	TBE	99.65–98.00	56.87–70.83	100.00–100.00	3514–3514
	SVM	97.29–97.53	65.90–67.07	99.35–99.26	3491–3488
	DT with CSLA	92.65–92.16	77.31–79.53	100.00–87.34	3514–3069
	TBE with CSLA	92.65–91.63	77.31–78.21	100.00–91.55	3514–3217
	SVM with CSLA	92.65–89.98	77.31–75.98	100.00–99.97	3514–3513

The first results were obtained for the imputation process that uses the pooled data. On the other hand, the second results were obtained when the imputation process was applied to both groups individually

ML Machine learning, *AUC* Area under curve, *DT* Decision tree classifier, *TBE* Tree-based ensemble classifier, *SVM* Support vector machine classifier, *CSLA* Cost-sensitive learning approach

Table 7 The comparison of the results of separately trained data and external validation

		Trained data		External validation	
		specificity (%)	Balanced accuracy (%)	Accuracy %	True positive
Acid	DT	83.63–80.12	66.24–75.29	88.67–88.65	3116–3115
	TBE	88.30–74.27	66.88–79.18	91.66–85.20	3221–2994
	SVM	76.02–74.85	66.99–66.40	89.50–89.19	3145–3134
	DT with CSLA	80.12–69.59	67.90–80.82	88.67–87.36	3116–3070
	TBE with CSLA	70.76–68.42	70.04–79.10	86.20–87.36	3029–3070
	SVM with CSLA	69.01–69.59	69.73–68.89	87.05–85.17	3059–2993
Alkaline	DT with CSLA	56.00–56.50	70.59–69.92	87.14–87.14	3062–3062
	TBE with CSLA	56.00–61.00	70.59–71.24	87.14–87.25	3062–3066
	SVM with CSLA	76.00–76.50	65.78–68.81	79.85–79.48	2806–2793

The first results were obtained for the imputation process that uses the pooled data. On the other hand, the second results were obtained when the imputation process was applied to both groups individually

ML Machine learning, *AUC* Area under curve, *DT* Decision tree classifier, *TBE* Tree-based ensemble classifier, *SVM* Support vector machine classifier, *CSLA* Cost-sensitive learning approach

various short and long-term complications [21, 22]. There are many studies in the literature that investigate the preoperative diagnosis of caustic burn, many of which mainly depend on the presence or absence of symptoms, nonetheless, the results are inconsistent.

Many factors affect the severity of the burn which are the type and the characteristics of the product, the pH degree, and the time frame until admission [23]. Furthermore, the concentration, time of contact, the ability of the penetration of the esophageal tissue, the fluid or solid content of the substance, and the organ's previous state are other major factors affecting the damage in the mucosa and then in the deeper layers [24]. The study evaluating 968 pediatric patients over 22 years in a center where early endoscopy was not performed routinely has shown that only 13.5% of all patients have developed esophageal strictures in the long term. However, 23% of patients who ingested the alkaline substance had a stricture lately which was higher compared to the acidic group.

Regarding the studies in the literature, the prediction of a burn is statistically significant when the severity of the burn is high, which only affects a tiny portion of the patient population. However, there was no statistically significant difference in the presence or lack of symptoms between individuals without burns and patients with mild and moderate burns. Although many efforts have been made to predict esophageal burn at admission, many studies in the literature have unnecessary endoscopy rates of between 60 and 80%

[5, 7, 8]. The validity of the history acquired from parents presents a significant challenge in determining the extent of the esophageal burn. Either there are no adult witnesses, or the parents are too concerned to notice the symptoms and signs that made the endoscopy inevitable. Regardless of the preference of the physician, one of the drawbacks of endoscopy is the inability to detect transmural or extra mucosal tissue damage. On the other hand, there is no confident predictor that determines the presence and severity of the burn before endoscopic evaluation, including the presence of oropharyngeal injuries [25, 26]. Therefore, since the symptoms and physical examination cannot be relied on to confirm the esophageal burn after caustic ingestion, many of the patients are missed or have unnecessary endoscopies not to miss. For instance, the study performed in a tertiary center in which physicians performed an endoscopy to evaluate the esophagus after corrosive ingestion has shown that 56.9% of the endoscopies were normal [27].

The current improvements in artificial intelligence with data mining in the processing of medical data and the revealing of the relation between examination and disease via advanced statistical methods prompt researchers to evaluate the existing data by using machine learning algorithms. However, there are certain drawbacks. The very first one is the inadequacy of the structured multicenter databases which results in the loss of the valuable amount of data. The second one is that these systems necessitate huge amounts of data whereas in caustic patients the number of cases decreases as the degree of burn increases.

Note that using the pooled data for the imputation of missing values may make the data noisy. On the other hand, the above-mentioned imputation process can be implemented for both groups individually resulting in an increase in bias. The results of machine learning methods for both imputation processes were utilized in the current study. In this case, it can be assumed that the realistic solution is between the results obtained for both imputation processes.

Since the alkaline substance proportion is considerably larger in the Control group, the effects of other variables except PDW might be suppressed in the training stage. The importance of PDW was found to be increased when the imputation process was applied to both groups individually. Accordingly, it may be speculated that the noise in the PDW values (due to the imputation process) disturbed the model and reduced the accuracy.

It should also be noted that the last results do not show which classifier is better for people with suspected caustic ingestion. They demonstrate that the classifiers trained with data containing only alkaline or acidic substances can be used not only for the people who take any caustic substances but also for the people who do not take them. Moreover, these classifiers are more successful for people who do not take caustic substances. This is an important point to be considered since there are pediatric patients who are unclear whether they have taken caustic substances in many cases.

The study has some drawbacks, one of which is that it uses a retrospective cohort analysis. Second, a small percentage of patients had burns, particularly severe esophageal burns.

Conclusion

Artificial intelligence systems have a high potential to be used in the management of healthcare problems. Taking into account that caustic substance ingestion has still mortality and morbidity, this study has promising results that preoperative burn prediction is viable in the management of the pediatric patient population.

Author contributions All authors contributed to the study conception and design. Material preparation and data collection were performed by all authors. Data analyses were performed by EA, BA and NK. The first draft of the manuscript was written by EA, BA and NK and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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