Title

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Authors

Rowe, Callum
Wiesendanger, Kathryn
Polet, Conner
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UC DAVIS SCHOOL OF MEDICINE

Temple University Lewis Katz School of Medicine

Callum Rowe,[1] Kathryn Wiesendanger,[1] Conner Polet,[2] Nathan Kuppermann, MD, MPH,[1] Stephen Aronoff, MD, MBA[2]

From the Department of Emergency Medicine[1], University of California, Davis School of Medicine, Sacramento, CA and the Department of Pediatrics[2], Lewis Katz School of Medicine at Temple University, Philadelphia, PA

BACKGROUND

- The Pediatric Emergency Care Applied Research Network (PECARN) conducted a study of ~42,000 children with minor blunt head trauma and developed and validated a clinical prediction rule to identify those at low risk of clinically-important traumatic brain injuries (ciTBIs) .[1]
- Prior studies have relied on traditional multivariable statistical methods,[1-2] but more recent research regarding prediction rules has used machine learning (ML).[3-6]
- In a previous study, investigators created a ML algorithm analyzing the PECARN dataset using a single decision tree that fits all nodes simultaneously, a complicated model at risk of over fitting.[6]
- In this study, we created multiple algorithms (see Table 2) using ML for classification of children at risk for ciTBIs via the PECARN head trauma public use dataset. The model predictions were statistically compared to no information rates, the error rate when the input and output are independent.

OBJECTIVES

To develop a clinical prediction tool using ML, for identifying children with ciTBIs after blunt head trauma that has superior prediction than the rules developed in PECARN's 2009 study.

METHODS

Table 1. PECARN Head Injury Prediction Variables

The PECARN head injury rule states that if a child, having suffered blunt force head trauma, has none of these clinical features they are considered very low-risk for a ciTBI.[1]

	Age < 2 Years	Age ≥ 2 Years
1.	Severe MOI*	Severe MOI*
2.	History of LOC ≥ 5 seconds	History of any LOC
3.	GCS < 15 or AMS	History of emesis
4.	Palpable/suspected skull fracture	GCS < 15 or AMS
5.	Tempero/parietal/occipital scalp hematoma	Severe headache
6.	Acting abnormally per parent	Signs of basilar skull fracture

MOI = Mechanism of Injury;
LOC = Loss of Consciousness;
GCS = Glasgow Coma Score;
AMS = Altered Mental Status;
PECARN = Pediatric Emergency Care Applied Research Network
*Severe mechanism defined by motor vehicle crash with patient ejection, death of another passenger, or rollover; pedestrian or bicyclist without helmet struck by a motorized vehicle; falls > 3 feet for those younger than 2 years; falls > 5 feet for those older than 2 years; or head struck by a high-impact object.

METHODS

Figure 1. Flowchart

Complete Data Set
N = 43,399; ciTBI = 763 (1.76%)

ciTBI status unknown
N = 20

N = 43,379;
ciTBI = 743 (1.76%)

GCS = 14,15
N = 41, 487

Clinically Apparent Skull Fracture
N = 381;
ciTBI = 67(14.9%)

GCS = 14
N = 1230; ciTBI = 77(6.2%)

GCS = 15
N = 39,876; ciTBI = 192(.48%)

- The PECARN public use data set included 43,399 patients <18 years-old with blunt head trauma at one of 25 pediatric Emergency Departments between 6/2004 and 9/2006.
- Clinical evidence of skull fractures were highly predictive of ciTBI and were not further evaluated.
- We divided the dataset into derivation (training) and validation (testing) subsets; four ML algorithms were optimized using the training dataset. Fitted models used the validation set to predict ciTBI and these predictions were compared statistically to the no information rate.

Table 2. ML Algorithms Utilized and their Functions

Algorithm	*Function*
Linear Regression (LR)	Provides a Linear Classifier
Classification and Regression Tree (CART)	Provides an optimized, single descion tree
Random Forest	An ensemble tree algorithm that tests a random selection of predictive variables for each node of multiple trees
Generalized Boosted Machine (GBM)	An ensemble tree algorithm that improves each iteration based on the prior tree

RESULTS

- For those patients without clinical evidence of skull fractures, the rates of ciTBI for GCS 14 and GCS 15 were significantly different (χ^2 = 604.02, p <.0001) and were modeled separately.

Table 4. Comparison of the no information model and ML algorithms as predictors of ciTBI in children with no clinical evidence of skull fractures and GCS scores of 14

Model	True Negative	False Negative	ciTBI Rate	p value
No information	392	26	0.062	1
Logistic Regression	389	26	0.063	1
CART	389	26	0.063	1
Random Forest	389	26	0.063	1
Generalized Boosted Model	392	26	0.062	1

ciTBI = clinically-important Traumatic Brain Injury,
CART = Classification and Regression Trees

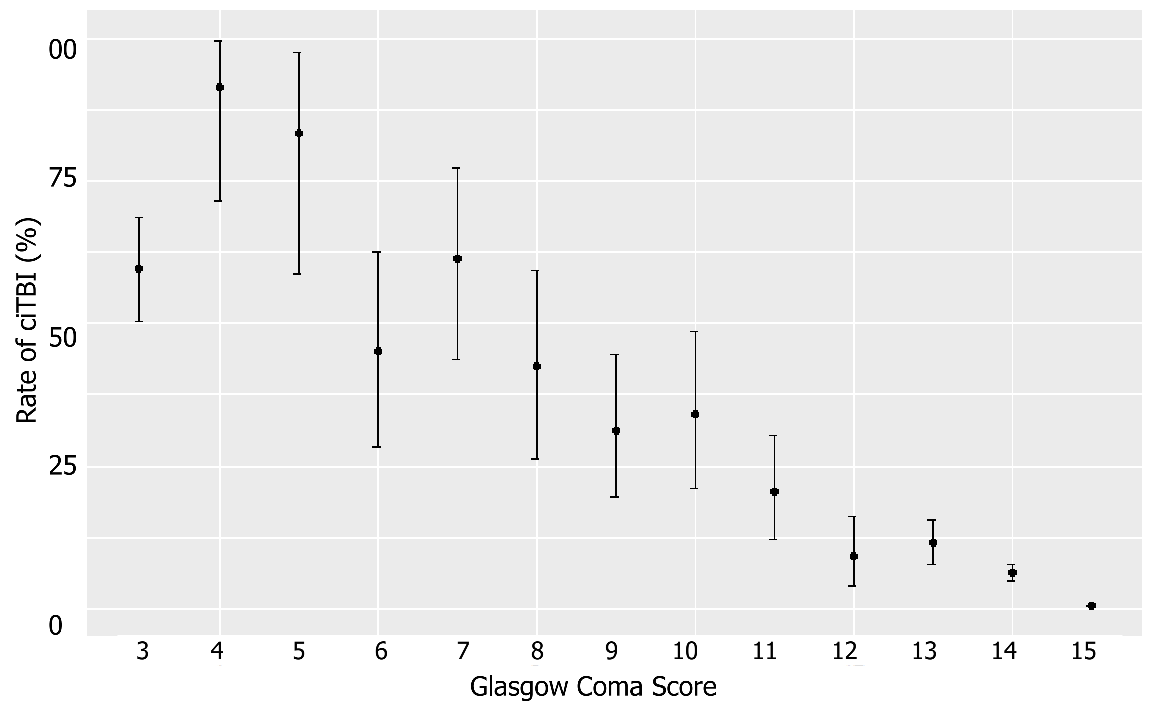
Table 5. Comparison of the no information model and ML algorithms as predictors of ciTBI, in children with no clinical evidence of skull fractures and GCS scores of 15

Model	True Negative	False Negative	ciTBI Rate	p value
No information	13492	65	0.00479	1
Logistic Regression	13492	65	0.00479	1
CART	13492	65	0.00479	1
Random Forest	13492	65	0.00479	1
Generalized Boosted Model	13492	65	0.00479	1

ciTBI = clinically-important Traumatic Brain Injury,
CART = Classification and Regression Trees

- None of the ML models was superior to the no information rate.

Figure 2. Relationship between ciTBI rates and GCS in children with no clinical evidence of skull fracture



CONCLUSIONS

- ML algorithms were unable to produce a superior prediction model for ciTBI among children with blunt head trauma when compared to PECARN's head injury prediction rule.
- GCS was the only important predictor identified by ML algorithms.

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