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Original Article

Application of machine learning to predict and identify factors associated with the need for surgery in traumatic epidural hematoma

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KEYWORDS

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Abstract:

Background: Timely identification of the need for surgical intervention in traumatic epidural hematoma (tEDH) is critical to optimizing outcomes. This retrospective study aimed to identify predictive factors for surgical intervention in tEDH using machine learning and develop a nomogram to support clinical decision-making.

Methods: In this retrospective study, data from 147 patients with tEDH at a major trauma center in western Iran (2023–2024) were analyzed. Demographic, Clinical, and CT scan data were extracted from medical records. Four machine learning models (Logistic Regression (LR)/ Support Vector Machine (SVM)/ Naive Bayes (NB)/Neural Network (NN)), were developed to predict surgical need. A Random Forest (RF) algorithm identified key predictors, and a nomogram was constructed from the LR model to facilitate individualized risk assessment. Statistical analyses were conducted using R software (version 4.3.2).

Results: In this study, 131 (89.1%) of 147 patients with tEDH were male. Of these, 72 (49%) underwent surgery. The cause of brain trauma was a Motor Vehicle Accident (MVA) in 76 (51.7%) of patients and a fall in 50 (34%) of patients. The mean (±Standard Deviation) age of the patients was 31.47 (±18.27). The initial hematoma volume demonstrated the highest discriminatory power, with an AUC of 0.92 (95% CI: 0.83–1.00) and an accuracy of 0.89 (95% CI: 0.76–0.96). The Glasgow Coma Scale (GCS) score also exhibited strong predictive performance, with an AUC of 0.76 (95% CI: 0.62–0.89) and an accuracy of 0.71 (95% CI: 0.56–0.84). The SVM model demonstrated the highest AUC of 0.96 (95% CI: 0.91–1.00), with sensitivity and specificity values above 90%.

Conclusion: In this study, the novel integration of machine learning with a nomogram offers clinicians a precise, user-friendly tool for rapid decision-making, potentially reducing complications. These findings help surgeons to make more informed clinical decisions by accurately assessing these parameters in the early stages and to identify patients at higher risk for surgical intervention more quickly.

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Introduction

Traumatic Brain Injury (TBI) is recognized as one of the most important global challenges.[1] TBI is a condition in which the brain is injured due to a blow or external force.[2] It can lead to disruption of normal brain function and a wide range of symptoms, from mild headaches to severe neurological disabilities and even death.[3] Most cases of TBI are mild TBI.[4] However, TBI remains a leading contributor to mortality and chronic disabilities.[5]

Annually, more than 64 to 74 million people worldwide suffer from TBI, indicating a high prevalence of this condition.[5] In Iran, TBI is also considered one of the main causes of trauma-related mortality and affects thousands of people each year.[6] The causes of TBI are diverse and include traffic accidents, falls from height, sports injuries, and intentional violence. [5] TBI may result in complications such as epidural hematomas, subdural hematomas, intracerebral hemorrhages, and subarachnoid hemorrhages (SAH). [7-9]

Epidural Hematoma (EDH) is an emergency and dangerous condition resulting from TBI, caracterized by the accumulation of blood in the epidural space. This condition is usually due to severe blows to the head that cause rupture of meningeal arteries, particularly the middle meningeal artery. [10] The most common clinical symptoms of EDH are vomiting, transient unconsciousness, followed by hemiparesis on the opposite side and pupil dilation on the same side. [11] If EDH is not drained and operated on in time, it can lead to the irreversible outcomes and even death. [12]

According to the results of a review study, the overall incidence of EDH worldwide is reported to be 8%, with approximately more than half of them (55.5%) who are often of working age requiring surgery. [13] Patients with EDH, if operated on in time, are generally treated with very favorable prognosis. [13] The mass effect resulting from the expansion of the epidural hematoma can lead to increased intracranial pressure and herniation. In such cases, timely emergency surgery is the only action that can save the patient from death. Therefore, making the right decision for early intervention before the volume of the epidural hematoma expands is crucial. [14]

Hematomas often require immediate surgical intervention for drainage and stopping the bleeding. However, recent studies show that in some cases, these hematomas can be successfully treated with non-invasive methods without the need for surgery. [15] The choice of treatment type, surgical or conservative, in EDH patients depends on their clinical and radiological outcomes. [16] For patients with hematoma, in addition to assessing neurological status, hematoma volume, patient age, and CT scan findings, in some cases, it may also depend on the judgment and choice of the neurosurgeon. [17-19] The consequences after TBI depend not only on the mechanism and severity of the mechanism and subsequent treatments but also on the individual characteristics of the injured individuals. On the other hand, given the high prevalence of TBI and the occurrence of hematoma and severe complications resulting from it in Iran and worldwide, the selection of immediate treatment methods for draining the hematoma or controlling bleeding is crucial. These actions can prevent more serious complications such as irreversible brain damage or even death. Conducting more studies in this area can contribute to the development of standard treatment protocols and improvement of clinical outcomes.

However, traditional statistical models often exhibit limitations in analyzing non-linear association and complex interactions between variables. In this regard, machine learning, with its ability to analyze complex data and identify hidden patterns, has been utilized as a novel solution. [20] This study aims to provide an optimal model for improving clinical decision-making by employing several machine learning models (LR/SVM/NN/ NB). A review of previous studies in this field indicates that the statistical models used in this study have not been utilized before for diagnosing the type of treatment. Therefore, this study was conducted with the objective of investigating the predictive factors for the need for surgical intervention in patients with traumatic epidural hematoma (tEDH), using various machine learning algorithms.

Methods

This study employed a retrospective design. the data and imaging records of patients with TBI, who were admitted to Taleghani Hospital in Kermanshah, the largest trauma center in western Iran, during the years 2023-2024 were examined. The study compared patients with tEDH who required surgical intervention with those who did not, aiming to identify risk factors influencing the choice of treatment (surgical vs. non-surgical). The collected data included demographic information : Age (years) and Gender (male / female), as well as clinical data related to the condition, including: Initial Hematoma Volume in CTscan (milliliters), Type of Trauma (Falling/Assault/(Motor Vehicle Accident(MVA);Subarachnoid Hemorrhage (no, yes); hematoma location (parietal, temporal, frontal, multiple); Petrous Temporal Bone Fracture (no, yes); Fracture (no, yes); Mixed Density (no, yes); Edema (no, yes); Air Density (no, yes);Brain Contusion (no, yes); Epidural Hematoma (EDH)/Subdural Hematoma (SDH)(no, yes); Major Cerebral Venous Sinus Fracture (no, yes);Skull Base Hematoma(no, yes) and Glasgow Coma Scale (GCS) score (quantitative). All brain CT-scans were performed at a single center using the same CT scanner, and the findings were interpreted by an experienced radiologist.

Inclusion criteria

Confirmation of traumatic epidural hematoma by a neurosurgeon.

Exclusion criteria

Incomplete case file information.

Exclusion of patients requiring surgical intervention who had significant intracranial injury or severe concomitant injuries (such as spinal cord injuries or multiple fractures).

Statistical Analysis

Software and Packages

Data preprocessing, statistical modeling, and visualization were performed using multiple R packages. The foreign, dplyr, tidyverse, tidyr, readxl, and haven packages were used for data handling and manipulation. Statistical tests were conducted using epiDisplay, oddsratio, DescTools, and OptimalCutpoints. Machine learning algorithms were implemented with randomForest, rpart, rpart.plot, e1071, rminer, Boruta, and neuralnet, while graphical visualization and nomogram development were performed using ggplot2, rms, and RColorBrewer. Statistical significance was defined as a p-value less than 0.05, and 95% confidence intervals (CIs) were calculated for all estimated model coefficients and performance metrics. All statistical analyses were conducted using R software (version 4.3.2).

Data Preprocessing

Continuous variables were normalized using the center and scale method from the caret package to ensure standardization across all predictors. A train_test split (70-30) was applied, where 70% of the data was used for model training and 30% for validation. Stratified random sampling was used to maintain proportional representation of the outcome variable (surgical vs. non-surgical cases) in both subsets.

Descriptive and Comparative Statistical Analysis

Descriptive statistics were calculated to summarize the baseline characteristics of the study population. Continuous variables were reported as mean (± standard deviation) or median (interquartile range) based on their normality, which was assessed using the Shapiro-Wilk test. Categorical variables were expressed as frequencies and percentages. Group comparisons were conducted using independent t-tests or Mann-Whitney U tests for continuous variables, depending on normality. For categorical variables, chi-square tests or Fisher's exact tests were used based on sample size distribution.

LR Analysis

A univariate LR analysis was performed to evaluate the association between each predictor and the need for surgical intervention. Each variable was analyzed independently using a binomial logit model. The predictive performance of individual factors was assessed by calculating the area under the receiver operating characteristic (ROC) curve (AUC), Sensitivity (SE), Specificity (SP), Positive Predictive Value (PPV), and Negative Predictive Value (NPV). The optimal cutoff value for classification was determined using Youden's Index, which identifies the threshold that maximizes both sensitivity and specificity. A multiple LR model was subsequently developed to assess the combined predictive ability of all variables. ROC analysis was conducted to evaluate model performance.

Feature Selection Using RF

A RF algorithm was applied to identify the most important predictors for surgical intervention. Hyperparameter tuning was performed using a grid search strategy, optimizing the number of trees (ntree), the number of variables randomly selected per split (mtry), the maximum number of nodes (maxnodes), and the minimum node size (nodesize). The Mean Decrease in Gini Index was used to rank variable importance. The top three predictors were identified through RF. These selected variables were used for further model development to enhance predictive efficiency and reduce model complexity.

Model Development

In this study, to classify patients based on the need for surgical intervention, four ML models were developed using the selected predictors. LR was used as a benchmark model, while SVM, NB, and NN were trained to improve classification performance. The SVM model was optimized by selecting the best kernel function and adjusting the cost (C) and gamma (γ) parameters. The NB model was implemented using conditional probability estimation. The NN model was trained using different hidden layer configurations, and optimal hyperparameters such as the number of neurons, learning rate, and activation function were determined through a systematic grid search approach.

Nomogram

A nomogram was developed based on the final LR model utilizing the rms package. This graphical tool provides a probability estimate of requiring surgical intervention based on patient-specific characteristics. The model was calibrated using bootstrapping techniques, and the calibration plot was examined to assess predictive reliability. The nomogram allows clinicians to estimate individualized risk and inform decision-making regarding surgical intervention.

Results

Baseline Characteristics of the patients

A total of 147 patients diagnosed with tEDH were included in the study. Among them, 72 (49.0%) required surgical intervention. Patients requiring surgery also had significantly lower GCS scores (median: 12.50, IQR: 6.00–14.00) than those treated conservatively (median: 15.00, IQR: 14.00–15.00) ($p<0.001$). Additionally, mixed-density hematoma, air density, and cerebral edema were significantly more prevalent among surgical cases ($p < 0.001$, $p = 0.003$, and $p < 0.001$, respectively), whereas other variables such as gender, type of trauma, and skull fractures showed no statistically significant associations (Table 1).

Table 1: Baseline Characteristics of Patients Based on Surgery

Variable	Levels	Total (n=147)	Surgery		P-value
			No (n=75)	Yes (n=72)	
Age	-----	31.48 ± 18.27	31.37 ± 18.76	31.60 ± 17.89	0.939
Initial Hematoma Volume in CT scan	-----	13.27 (5.06, 47.17)	6.30 (2.92, 11.81)	47.17 (18.63, 73.24)	<0.001
Glasgow Coma Scal	-----	14.00 (11.00, 15.00)	15.00 (14.00, 15.00)	12.50 (6.00, 14.00)	<0.001
Gender	Female	16 (10.88)	11 (14.67)	5 (6.94)	0.133
	Male	131 (89.12)	64 (85.33)	67 (93.06)	
Hematoma Location	Frontal-Occipital-Temporal	18 (12.24)	8 (10.67)	10 (13.89)	0.551
	Multiple areas	129 (87.76)	67 (89.33)	62 (86.11)	
Type of Trauma	Falling	50 (34.01)	28 (37.33)	22 (30.56)	0.060
	Assault	13 (8.84)	10 (13.33)	3 (4.17)	
	MVA	84 (57.14)	37 (49.33)	47 (65.28)	
Fracture	No	39 (26.53)	24 (32.00)	15 (20.83)	0.125
	Yes	108 (73.47)	51 (68.00)	57 (79.17)	
Petrous Temporal Bone Fracture	No	127 (86.39)	66 (88.00)	61 (84.72)	0.562
	Yes	20 (13.61)	9 (12.00)	11 (15.28)	
Mixed Density	No	79 (53.74)	54 (72.00)	25 (34.72)	<0.001
	Yes	68 (46.26)	21 (28.00)	47 (65.28)	
Air Density	No	93 (63.27)	56 (74.67)	37 (51.39)	0.003
	Yes	54 (36.73)	19 (25.33)	35 (48.61)	
Brain Contusion	No	104 (70.75)	54 (72.00)	50 (69.44)	0.733
	Yes	43 (29.25)	21 (28.00)	22 (30.56)	
Subarachnoid Hemorrhage	No	103 (70.07)	52 (69.33)	51 (70.83)	0.843
	Yes	44 (29.93)	23 (30.67)	21 (29.17)	
EDH/SDH	No	123 (83.67)	62 (82.67)	61 (84.72)	0.736
	Yes	24 (16.33)	13 (17.33)	11 (15.28)	
Edema	No	92 (62.59)	65 (86.67)	27 (37.50)	<0.001
	Yes	55 (37.41)	10 (13.33)	45 (62.50)	
Major Cerebral Venous Sinus Fracture	No	141 (95.92)	73 (97.33)	68 (94.44)	0.376
	Yes	6 (4.08)	2 (2.67)	4 (5.56)	
Skull Base Hematoma	No	136 (92.52)	71 (94.67)	65 (90.28)	0.312
	Yes	11 (7.48)	4 (5.33)	7 (9.72)	

Note: Baseline demographic and clinical characteristics of patients with traumatic epidural hematoma are presented, stratified by treatment type (surgical vs. non-surgical). Continuous variables are reported as mean (± standard deviation) or median (interquartile range), and categorical variables as frequency (percentage). Statistical significance was assessed using the independent t-test or Mann-Whitney U test for continuous variables and the chi-square test or Fisher's exact test for categorical variables.

Predictive Performance of Individual Clinical and Radiological Factors

The diagnostic ability of individual variables in predicting surgical intervention was evaluated using ROC analysis. The initial hematoma volume demonstrated the highest discriminatory power, with an AUC of 0.92 (95% CI: 0.83–1.00) and an accuracy of 0.89 (95% CI: 0.76–0.96). The GCS score also exhibited strong predictive performance, with an AUC of 0.76 (95% CI: 0.62–0.89) and an accuracy of 0.71 (95% CI: 0.56–0.84). In contrast, demographic variables such as age and gender showed poor predictive ability (AUC < 0.60). Among radiological findings, the presence of cerebral edema had an AUC of 0.75 (95% CI: 0.63–0.87) (Table 2).

The importance of these clinical and radiological factors in predicting surgical intervention is depicted in Figure 1. The analysis highlights that the initial hematoma volume, GCS and presence of cerebral edema are the most influential predictors, whereas age and gender contribute minimally to the decision-making process.

Model Performance

The predictive performance of ML models was assessed to determine their ability to classify patients based on the need for surgery. The LR model using all variables achieved an AUC of 0.94 (95% CI: 0.87–1.00), whereas the model using selected variables (initial hematoma volume, GCS, and presence of cerebral edema) had a similar AUC of 0.94 (95% CI: 0.87–1.00) but improved specificity (0.87 vs. 0.74). The SVM model demonstrated the highest AUC of 0.96 (95% CI: 0.91–1.00), with sensitivity and specificity values

Table 2: Predictive Performance of Individual Variables for Surgical Intervention.

Variables	AUC (95% CI)	SE (95% CI)	SP (95% CI)	PPV (95% CI)	NPV (95% CI)	Accuracy (95% CI)
Age	0.42 (0.24,0.60)	0.14 (0.05,0.33)	1.00 (0.86,1.00)	1.00 (0.44,1.00)	0.55 (0.40,0.69)	0.56 (0.40, 0.70)
Initial Hematoma Volume in CT scan	0.92 (0.83,1.00)	0.91 (0.72,0.97)	0.87 (0.68,0.95)	0.87 (0.68,0.95)	0.91 (0.72,0.97)	0.89 (0.76, 0.96)
Glasgow Coma Scale	0.76 (0.62,0.89)	0.77 (0.57,0.90)	0.65 (0.45,0.81)	0.68 (0.48,0.83)	0.75 (0.53,0.89)	0.71 (0.56, 0.84)
Gender	0.56 (0.46,0.67)	0.91 (0.72,0.97)	0.22 (0.10,0.42)	0.53 (0.37,0.68)	0.71 (0.36,0.92)	0.51 (0.36, 0.66)
Trauma Type (Assault vs. Falling)	0.57 (0.49,0.64)	1.00 (0.85,1.00)	0.13 (0.05,0.32)	0.52 (0.38,0.67)	1.00 (0.44,1.00)	0.56 (0.40, 0.70)
Trauma Type (MVA vs. Falling)	0.56 (0.41,0.70)	0.55 (0.35,0.73)	0.57 (0.37,0.74)	0.55 (0.35,0.73)	0.57 (0.37,0.74)	0.56 (0.40, 0.70)
Hematoma Location	0.48 (0.37,0.59)	1.00 (0.85,1.00)	0.00 (0.00,0.14)	0.49 (0.35,0.63)	NA (NA, NA)	0.49 (0.34, 0.64)
Fracture	0.54 (0.43,0.65)	0.86 (0.67,0.95)	0.22 (0.10,0.42)	0.51 (0.36,0.67)	0.63 (0.31,0.86)	0.51 (0.36, 0.66)
Petrous Temporal Bone Fracture	0.50 (0.39,0.62)	0.18 (0.07,0.39)	0.83 (0.63,0.93)	0.50 (0.22,0.78)	0.51 (0.36,0.67)	0.51 (0.36, 0.66)
Mixed Density	0.67 (0.53,0.81)	0.64 (0.43,0.80)	0.70 (0.49,0.84)	0.67 (0.45,0.83)	0.67 (0.47,0.82)	0.67 (0.51, 0.80)
Air Density	0.71 (0.58,0.84)	0.64 (0.43,0.80)	0.78 (0.58,0.90)	0.74 (0.51,0.88)	0.69 (0.50,0.83)	0.71 (0.56, 0.84)
Brain Contusion	0.34 (0.23,0.45)	1.00 (0.85,1.00)	0.00 (0.00,0.14)	0.49 (0.35,0.63)	NA (NA, NA)	0.49 (0.34, 0.64)
Subarachnoid Hemorrhage	0.45 (0.34,0.57)	1.00 (0.85,1.00)	0.00 (0.00,0.14)	0.49 (0.35,0.63)	NA (NA, NA)	0.49 (0.34, 0.64)
EDH/SDH	0.41 (0.31,0.51)	1.00 (0.85,1.00)	0.00 (0.00,0.14)	0.49 (0.35,0.63)	NA (NA, NA)	0.49 (0.34, 0.64)
Edema	0.75 (0.63,0.87)	0.59 (0.39,0.77)	0.91 (0.73,0.98)	0.87 (0.62,0.96)	0.70 (0.52,0.83)	0.51 (0.36, 0.66)
Major Cerebral Venous Sinus Fracture	0.50 (0.44,0.56)	0.05 (0.01,0.22)	0.96 (0.79,0.99)	0.50 (0.09,0.91)	0.51 (0.37,0.65)	0.51 (0.36, 0.66)
Skull Base Hematoma	0.52 (0.45,0.60)	0.09 (0.03,0.28)	0.96 (0.79,0.99)	0.67 (0.21,0.94)	0.52 (0.38,0.67)	0.53 (0.38, 0.68)

Note: Predictive performance of various clinical and radiological factors in determining the need for surgical intervention in patients with traumatic epidural hematoma is presented. Metrics such as AUC, SE, SP, PPV, NPV, and ACC are reported with their respective 95% confidence intervals. ROC curve analysis was used to determine AUC values.

above 90%. The NN model achieved an AUC of 0.92 (95% CI: 0.81–1.02), while the NB model showed an AUC of 0.93 (95% CI: 0.87–1.00), with a high specificity of 0.96 (95% CI: 0.79–0.99) (Table 3). Figure 2 illustrates the ROC curves of the machine learning models, emphasizing that the SVM model outperformed other classifiers in terms of predictive accuracy.

Finally, Figure 3 presents a nomogram developed to estimate the probability of surgical intervention based on key clinical and radiological variables.

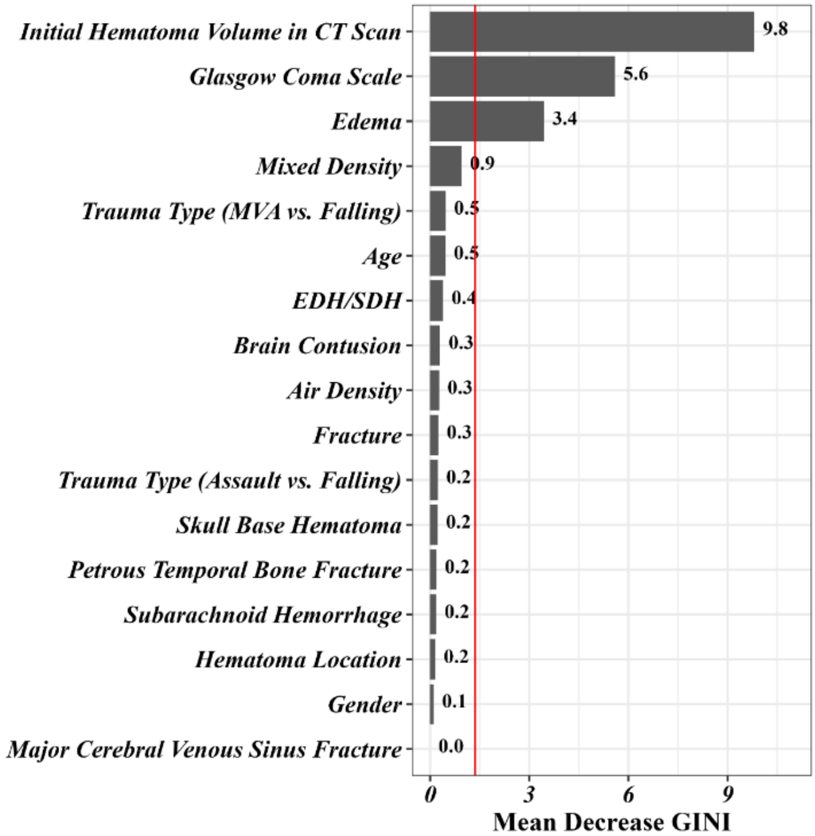

Figure 1: Variable Importance in Predicting the Need for Surgical Intervention

Table 3: Performance of Machine Learning Models in Predicting Surgical Intervention

Variables	AUC (95% CI)	SE (95% CI)	SP (95% CI)	PPV (95% CI)	NPV (95% CI)	ACC (95% CI)
LR - Total	0.94 (0.87, 1.00)	1.00 (0.85, 1.00)	0.74 (0.54, 0.87)	0.79 (0.60, 0.90)	1.00 (0.82, 1.00)	0.84 (0.71, 0.94)
LR - Selected variables	0.94 (0.87, 1.00)	0.91 (0.72, 0.97)	0.87 (0.68, 0.95)	0.87 (0.68, 0.95)	0.91 (0.72, 0.97)	0.89 (0.76, 0.96)
SVM - Selected variables	0.96 (0.91, 1.00)	0.91 (0.72, 0.97)	0.91 (0.73, 0.98)	0.91 (0.72, 0.97)	0.91 (0.73, 0.98)	0.89 (0.76, 0.96)
NB - Selected variables	0.93 (0.87, 1.00)	0.82 (0.61, 0.93)	0.96 (0.79, 0.99)	0.95 (0.75, 0.99)	0.85 (0.66, 0.94)	0.89 (0.76, 0.96)
NN - Selected variables	0.92 (0.81, 1.02)	0.91 (0.72, 0.97)	0.96 (0.79, 0.99)	0.95 (0.77, 0.99)	0.92 (0.74, 0.98)	0.93 (0.82, 0.99)

Note: Comparison of the predictive performance of different ML models, including LR, SVM, NB, and NN, using selected clinical and radiological variables. The evaluation metrics include AUC, sensitivity, specificity, PPV, NPV, and accuracy, with corresponding 95% confidence intervals. Model performance was assessed using cross-validation techniques.

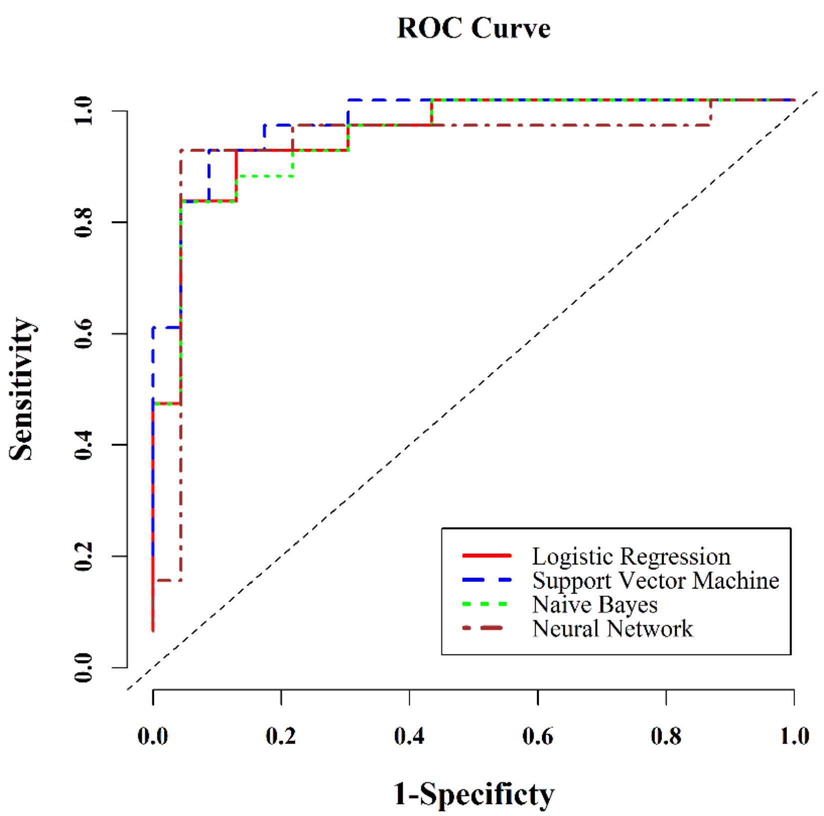

Figure 2: ROC Curves for Machine Learning Models in Predicting Surgical Intervention

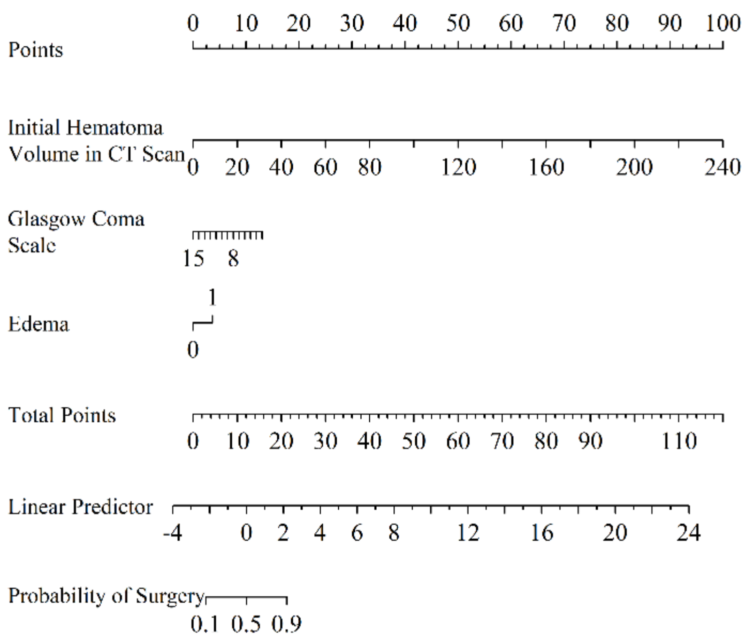

Figure 3: Nomogram for Predicting the Probability of Surgical Intervention

Discussion

This retrospective study demonstrates the efficacy of ML models in predicting the need for surgical intervention in patients with tEDH, identifying initial hematoma volume, GCS score, as key predictors. The SVM model achieved an exceptional AUC of 0.96 (95% CI: 0.91–1.00), surpassing traditional LR approaches. These findings align with Brain Trauma Foundation guidelines, which emphasize hematoma volume (>30 mL) and low GCS (<9) as critical indicators for surgery. [21] However, our integration of multiple ML models and a novel nomogram distinguishes this study, offering a practical tool for rapid, individualized risk stratification in emergency settings.

Compared to prior ML studies in TBI, our work addresses a unique niche. Hasanpour et al. utilized ML to predict hematoma expansion in tEDH, reporting an AUC of 0.89, but did not focus on surgical decision-making or develop a nomogram. [22] Similarly, Fuse et al. (2022) applied ML to predict unfavorable functional outcomes in chronic subdural hematoma, achieving an AUC of 0.86, yet their focus on a different hematoma type limits direct comparability. [23] To the best of our knowledge at the time of writing, no study has simultaneously utilized machine learning algorithms and nomograms to predict the need for surgical intervention in patients with tEDH. This research gap underscores the novelty and clinical significance of our study, which provides a precise and user-friendly tool for clinical decision-making in emergency settings.

In this study, 131 patients (89.1%) were male, and 76 patients (51.7%) had trauma due to accidents. The study by Offner et al. also showed that 68 patients (81%) with epidural hematoma were male, and the most common mechanism of injury was falling. [24] In Choi et al.'s study, 81 patients (83%) were male, and MVAs were the most common mechanism of trauma. [25] Additionally, another study found that most trauma cases were in males (51 patients, 81%), and the most common mechanism of trauma was accidents. This study, similar to previous research, showed that epidural hematoma is more prevalent in males, and traffic accidents are one of the main causes. Males are more exposed to high-risk activities, including high-speed driving, industrial work, risky sports, and drinking while driving, which increase the likelihood of trauma. These findings emphasize the need for implementing programs to prevent traffic accidents, raise public awareness, and modify high-risk behaviors in males. They can also be useful in treatment strategies and clinical decision-making for managing trauma patients.

In our study, the mean age of victims with tEDH was 31.56 years, and age did not have a significant association with the type of management. The study by Offner et al. also showed that the mean age of patients with epidural hematoma was 27 years, and age did not affect the type of treatment. [24]

However, in studies by Choi et al. [25] and Hasanpour et al.[22] older age was associated with unfavorable outcomes. Based on various studies and their contradictions, it seems that age alone cannot predict the type of treatment in tEDH patients, but it may influence the long-term prognosis of patients. Conducting a meta-analysis to determine the effect of age is recommended.

The results of this study showed, the mean hematoma volume in patients who underwent surgery was 55.45 ml, which was significantly higher than the mean volume in the conservative treatment group (8.86 ml). In Dharma et al.'s study, the mean hematoma volume was 30.5 ml. [26] Bullock et al.'s study showed that an epidural hematoma volume greater than 30 ml, even in patients with stable neurological status, should be considered for surgery. Their results also emphasized that hematoma volume is directly related to the risk of increased ICP and the need for surgical intervention.[16] Based on the results of Hasanpour et al.'s study high initial EDH volume influenced hematoma expansion and the need for surgical intervention. [22] In Offner et al.'s study, 54 (64%) patients were initially managed non-surgically, and 30 (36%) were directly taken to the operating room for craniotomy.[24] Non-surgical management was successful in 47/54 patients (87%).[24] The results of this study and previous studies clearly show that epidural hematoma volume (typically greater than 30 ml) acts as a key criterion for selecting emergency surgery. These findings are consistent with the Brain Trauma Foundation guidelines, which consider high hematoma volume, even in patients without severe symptoms, as requiring surgical intervention. [16] Epidural hematoma, due to blood accumulation in the epidural space, can cause increased intracranial pressure. Initial hematoma volume is one of the most important imaging parameters that plays a key role in deciding between surgical and non-surgical treatment in patients with tEDH. This parameter is directly related to intracranial pressure (ICP) and the risk of neurological damage. Initial hematoma volume not only plays a role in treatment decisions but also serves as a predictive factor for patient prognosis. In cases where the initial hematoma volume is less than 30 milliliters and the patient is neurologically stable, non-surgical treatment may be considered. However, even in these cases, patients must be closely monitored, as epidural hematoma may suddenly progress.

In this study, the mean GCS score in individuals who underwent surgery was 10.54, which was lower than that of the conservative treatment group. The results of the study by Dharma et al. showed that the volume of EDH is significantly associated with the GCS score in head injury patients. Larger EDH volumes are associated with lower GCS scores. [26] The results of the study by Bullock et al. suggest that a low GCS (GCS score < 9) should be considered an independent indicator for the need for surgery in patients with acute epidural hematoma. [16] In the study by Choi et al., a lower initial GCS score and a larger EDH volume were associated with unfavorable outcomes. [25]

Patients with a moderate GCS (moderate brain injury) may require surgery, but this decision also depends on other factors such as hematoma volume, the patient's clinical status, and imaging results. [17-19] The GCS was first developed in 1974 by two neurosurgeons, Teasdale and Jennett, at the University of Glasgow, as an index for evaluating the level of consciousness in head trauma. This scale, based on three components eye response, verbal response, and motor response—enables the classification of brain injury severity, prediction of patient outcomes, and guidance of treatment decisions. A low GCS score is a strong prognostic indicator, directly associated with clinical outcomes including mortality, secondary complications, and persistent neurological deficits; accordingly, lower scores indicate the need for immediate interventions. [27-29] Based on the results obtained, the patient's neurological status, evaluated using the GCS, plays a crucial role in determining whether surgical or non-surgical treatment is appropriate for patients with traumatic epidural hematoma.

Some older studies concluded that immediate evacuation of the hematoma immediately after diagnosis plays a key role in preventing irreversible neurological complications and identified delay in surgery as the primary risk factor for unfavorable outcomes.[30] However, contemporary research evidence suggests that in selected cases, non-surgical management can also be effective. The study by Zakria et al. showed that in patients with stable neurological symptoms and a stable GCS score, conservative management of extradural hematoma is possible. [31] On the other hand, Kulwant Singh et al. proposed more precise criteria, including GCS >12, hematoma volume less than 10 milliliters, and no involvement of the temporal region, for conservative management. [32]

A critical point in this approach is the continuous monitoring of patients, as the expansion of hematomas such as epidural and extradural typically occurs within a 36-hour period after trauma, with the peak reported in the middle of the first 8 hours. [33] According to the results of this study, the presence of edema had a significant effect on the need for immediate surgery in EDH patients. Additionally, several studies have identified the presence of brain lesions as a factor influencing unfavorable outcomes after surgery in EDH patients. [34-39]

In the study by Aromatario et al., [40] along with other factors, the presence of edema was also mentioned as one of the factors worsening the prognosis of trauma patients with epidural and subdural hematoma. There are fewer studies on the effect of edema on prognosis and unfavorable outcomes in patients with EDH. However, in general, it can be said that the presence of edema in the epidural space or within the skull is usually indicative of a severe head injury. This phenomenon may be associated with serious structural injuries such as skull fracture, air sinus rupture, or brain tissue damage. These injuries typically require surgical intervention.

Conclusion

In this study, the need for surgical intervention in tEDH has been addressed through a novel approach integrating ML algorithms with a user-friendly nomogram. A visually intuitive tool has been developed to facilitate rapid and informed decision-making in emergency settings. The identification of patients requiring urgent surgery is supported, while non-surgical management is enabled for those with stable conditions, provided close monitoring with serial imaging and neurological assessments is conducted.

Limitations

The findings of this study are subject to several limitations that warrant consideration. Firstly, the retrospective design restricted access to comprehensive clinical data, such as comorbidities and temporal changes in patient status, potentially influencing the predictive model's robustness. Secondly, the study was conducted at a single trauma center, which may restrict the applicability of the findings to broader settings. Thirdly, the relatively modest sample size may have constrained the statistical power and the ability to detect nuanced associations among predictors.

Suggestions

To address these limitations, several avenues for future research are recommended. Multicenter prospective studies are suggested to enhance the generalizability of the nomogram and validate its performance across varied populations. The incorporation of additional clinical variables, such as biomarkers, is proposed to refine the predictive accuracy. These efforts will strengthen the applicability of this novel approach to tEDH management.

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