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# The Field Attributes May not Accurately Predict the Need for Early Tracheostomy Tube Insertion in Severe TBI Patients: A New Insight With the Help of AI Algorithms

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## ABSTRACT

**Objective:** Traumatic brain injury (TBI) patients often require prolonged intubation, and tracheostomies are often performed in intensive care units (ICUs) for patients who require prolonged ventilator support. Tracheostomy tube insertion can facilitate weaning in patients who require prolonged ventilation, leading to a decrease in mechanical ventilation duration and the length of stay in the intensive care unit. Additionally, it minimizes complications associated with extended tracheal intubation. There is a lack of data on determining which individuals will necessitate tracheostomy. Our objective was to predict tracheostomy requirements using patient data at arrival.

**Methods:** We used a retrospectively collected data set of a large number of patients, who had been admitted to neuro-ICU Emtiaz Hospital, a large tertiary center of trauma. We trained several machine learning (ML) models in conjunction with initial predictors such as age, Glasgow comma scale (GCS), Rotterdam score, pupil response, first blood sugar, shift, and intracranial hematoma. The ML methods we used and compared were Logistic regression, random forest (RF), Gradient boosting machines (GBT), and multilayer perceptron (MLP).

**Results:** 546 patients including 282 negatives (who did not receive tracheostomy) and 264 positives (who did receive tracheostomy) were included in our study. We randomly divided the data set into 70% for training and 30% for testing. The logistic regression predicted tracheostomy with a lower AUC (0.61) as compared to RF (AUC 0.64), MLP (AUC 0.65), and GBT (AUC 0.66).

**Conclusions:** Our study aimed to create an ML model for predicting TTI in severe TBI patients. Despite using recognized predictors, the best model achieved an AUC of 0.66, indicating the inherent complexity in prediction. The findings serve as a valuable starting point for developing a predictive model and reassessing factors in the clinical setting that may not reliably predict tracheostomy needs at admission.

## 1 | Introduction

Traumatic brain injury (TBI) holds the highest occurrence among prevalent neurological disorders and presents a significant public health challenge. TBI is estimated to occur in 50 million cases globally, indicating that approximately half of the worldwide population will experience a TBI at some point in their lifetime [1]. In low- and middle-income countries (LMICs), TBI occurrences are predominantly influenced by road traffic accidents, often affecting vulnerable road participants like motorcyclists and pedestrians [2]. Inadequate access to health-care services and shortage of intensive care units (ICU) Bring about crucial impact on the outcome of severe TBI patients causing noticeable death toll ensuing severe TBI [2, 3].

Endotracheal intubation is frequently required in patients with TBI to maintain airway openness and prevent oxygen deficiency [3]. Tracheostomy can help patients on prolonged mechanical ventilation wean, reducing the length of stay in the ICU and reducing complications associated with extended endotracheal intubation [4]. Key reasons for considering a tracheostomy tube insertion (TTI) in TBI cases include difficulties weaning, the absence of protective airway reflexes, compromised respiratory drive, and difficulties managing secretions [5]. Since Severe TBI patients frequently require mechanical ventilation and admission to ICU [6], early TTI appears to be an attractive option in terms of mitigating the subsequent complications of prolonged Endotracheal Tube (ETT) intubation including Ventilator-associated Pneumonia (VAP) and longer ICU stay due to difficulties pertaining to wean the patients [7]. Nevertheless, as TTI procedures encompass certain complications, several predictive factors considering patient, diagnostic, and intervention-related variables have been acknowledged [8, 9].

Machine learning (ML) algorithms have witnessed a significant surge due to the rapid advancement of software. ML techniques have been extensively employed in medicine, yielding promising outcomes by developing predictive algorithms for various medical conditions [10–12]. Traditional predictive models typically utilize a limited number of selected parameters, whereas ML methods can incorporate multiple clinical parameters [13]. Some studies aimed to predict the need for tracheostomy in several conditions using artificial intelligence [14–16]. Speaking of ML accountability in predicting medical conditions, a number of clinical parameters such as ICU-diagnosed pneumonia along with mechanical ventilation duration have been introduced to date representing the need for TTI. Nevertheless, these studies have lacked a focus on parameters specific to severe TBI and have not provided conclusive frameworks for early TTI prediction [17]. In this study, we employed several ML algorithms to predict the need for tracheostomy in severe TBI patients. Specifically, we selected models such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting due to their ability to handle both structured and unstructured data effectively and their proven performance in classification tasks involving medical datasets. Currently, no ML model has been designed to assist physicians in predicting which patients will need tracheostomy upon emergency department arrival in severe TBI cases. Consequently, our objective was to develop an ML-based model using admission variables, such as age, Glasgow Coma Scale (GCS), Rotterdam score, pupil response, first blood sugar, midline shift, and intracranial hematoma, to predict the necessity for tracheostomy in severe TBI patients at a tertiary center.

## 2 | Methods

### 2.1 | Study Design and Setting

This retrospective study was carried out in the neuro-ICU of Emtiaz Hospital, Shiraz, Iran. This tertiary ICU admits neurosurgery patients such as clinical cases or surgical patients. The study protocol was approved by the Research Ethics Committee of Shiraz University of Medical Sciences.

### 2.2 | Patients and Collected Variables

All the patients admitted to our neuro-ICU between April 2017 and March 2022, who met our inclusion and exclusion criteria were included in this study. Our patients were divided into 2 groups: non-tracheostomized and tracheostomized. All tracheostomies were performed exclusively in the operating room. The indications and timing of tracheostomy were made based on clinical decisions and hospital protocols. All tracheostomies were performed within a timeframe of less than 7 days from the initial ED presentation.

Inclusion criteria for participants were as follows: (1) All patients have Abbreviated Injury Scale (AIS) brain > 3 at admission, (2) Age 14 years and older, (3) Isolated blunt head injury.

Exclusion criteria were: (1) Any need for a non-neurosurgical operation, (2) developmental delay patients, (3) Polytrauma causing unstable hemodynamic status, (4) Other organ AIS > 3, (5) Age > 65.

Two neurosurgeons carefully gathered comprehensive medical records from patients. The collected data encompassed various aspects of the emergency room, such as demographics, clinical, and first brain CT features. The predictors included: Demographics and clinical features: Age, gender, initial Glasgow Coma Scale (GCS), initial motor GCS, pupil response to light on arrival, Rotterdam score, and first blood sugar. First CT scan variables: Radiological findings from the initial brain CT scan were included, such as midline shift, subarachnoid hemorrhage (SAH), intraventricular hemorrhage (IVH), basal skull fractures, pneumocephalus, epidural hematoma (EDH), subdural hematoma (SDH), and intracerebral hemorrhage (ICH). These variables were selected based on their clinical relevance and availability in the emergency setting, aiming to ensure the model's practicality and applicability in real-time decision-making.

### 2.3 | Model Development

In our predictive modeling approach to assess the necessity for tracheostomy in severe TBI patients, we employed a diverse set of machine learning (ML) algorithms: Logistic Regression (LR), Random Forest (RF), Gradient Boosting Machines (GBT), and Multilayer Perceptron (MLP). The selection of these algorithms was guided by their complementary strengths in addressing the complexity and heterogeneity of medical datasets.

Logistic regression (LR): LR was utilized as a baseline model due to its simplicity and interpretability. It models the probability of a binary outcome, in this case, the need for tracheostomy, as a function of the input features. LR provides clear insights into the contribution of each predictor, making it an ideal starting point for comparison with more complex models.

Random forest (RF): RF, an ensemble learning method, was employed to capture complex nonlinear relationships within the data. RF operates by constructing multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) from all the trees. It is particularly effective in handling high-dimensional data, addressing potential overfitting, and managing missing data. We optimized key parameters, including the number of trees, maximum tree depth, and minimum samples per leaf, and cross-validation.

Gradient boosting machines (GBM): GBM was included for its ability to combine weak learners iteratively into a strong predictive model. GBM excels in improving predictive accuracy, especially for imbalanced datasets. By optimizing parameters such as learning rate, the number of boosting stages, and the maximum depth of trees, we ensured the model's performance and generalizability.

Multilayer perceptron (MLP): The MLP, a type of artificial neural network, was leveraged to detect intricate patterns and relationships within the data. MLP is especially adept at capturing complex interactions among predictors that may not be apparent through traditional models. Key hyperparameters such as the number of hidden layers, the number of neurons per layer, the activation function, and the learning rate were fine-tuned to enhance the model's predictive capabilities.

By leveraging the strengths of these diverse algorithms, our predictive model aimed to enhance the accuracy and reliability of identifying the need for tracheostomy, contributing to more informed clinical decision-making.

## 3 | Statistical Analysis

### 3.1 | Data Analysis

Demographic and clinical characteristics were compared between non-tracheostomized and tracheostomized patients. For quantitative variables, the Mann–Whitney test was used, as it is a non-parametric test suited for comparing medians between two groups when the data are not normally distributed. For qualitative variables, the Fisher exact test was applied due to its accuracy in small sample sizes. All quantitative variables are presented as medians with interquartile ranges (IQR), while qualitative variables are reported as numbers and percentages. Statistical analyses were performed using IBM SPSS Statistics (version 20), and a significance level of $p < 0.05$ was considered statistically significant.

### 3.2 | Model Evaluation

The performance of our machine learning models was assessed using four evaluation metrics: accuracy, precision, recall, and F1 score. Given the clinical context of this study, where both false positives (unnecessary tracheostomies) and false negatives (delayed necessary tracheostomies) carry significant implications, the F1 score was prioritized as the primary evaluation metric. This approach ensured that both precision and recall were equally emphasized to minimize the risks associated with misclassification.

## 4 | Results

### 4.1 | Patients

A total of 546 patients with TBI were included. The age was $38.31 \pm 18.36$ years (Mean $\pm$ standard deviation), with 88.1% being male. Within the cohort, 264 individuals (48.35%) underwent tracheostomies, while 282 (51.65%) did not. Further information on the study patients' characteristics is outlined in Table 1.

### 4.2 | Models Performance

We initially randomly divided the data set into 70% for training and 30% for testing. To assess the predictive efficacy of each machine learning (ML) model, we initially conducted ten-fold cross-validation on the data set. The results revealed that the MLP exhibited the highest F1 score at 60%. Furthermore, the MLP also demonstrated the highest sensitivity at 64%, while LR achieved the highest specificity at 64%. Regarding positive predictive value (PPV), both MLP and GBT achieved the highest score at 58%, whereas MLP achieved the highest negative predictive value (NPV) at 63% (see Table 2). The receiver operating characteristic (ROC) curves for each algorithm, illustrated in Figure 1, indicated that the GBT outperformed others with the highest area under the curve (AUC) at 0.66. Additionally, Figure 2 presents the confusion matrices for the various models, providing a comprehensive overview of their performance characteristics.

## 5 | Discussion

Exploring the predictive capabilities of traditional field attributes in determining the need for early tracheostomy in severe TBI patients revealed potential limitations. Our investigation, guided by AI algorithms, provides an unprecedented perspective on this critical medical decision. ML models discovered intricate patterns and complex relationships within the data set, implying that traditional indicators may not consistently and accurately predict the need for an early tracheostomy. While there is no established guideline for predicting the need for early tracheostomy based on initial data at arrival,

**TABLE 1** | Baseline characteristics of patients.

| Variables | | Total (546) | Nontracheostomy (282) | Tracheostomy (264) | *p* value |
|---|---|---|---|---|---|
| Age | | $38.31 \pm 18.36$ | $39.50 \pm 20.072$ | $37.03 \pm 16.279$ | 0.000 |
| Gender (F) | | | | | 0.706 |
| | Female | 65 (11.9%) | 35 (12.4%) | 30 (11.4%) | |
| | Male | 481 (88.1%) | 247 (87.6%) | 234 (88.6%) | |
| mGCS | | | | | 0.000 |
| | 1 | 267 (48.9%) | 161 (57.1%) | 106 (40.2%) | |
| | 2 | 128 (23.4%) | 50 (17.7%) | 78 (29.5%) | |
| | 3 | 151 (27.7%) | 71 (25.2%) | 80 (30.3%) | |
| GCS | | | | | 0.001 |
| | 3 | 258 (47.3%) | 156 (55.3%) | 102 (38.6%) | |
| | 4 | 128 (23.4%) | 50 (17.7%) | 78 (29.5%) | |
| | 5 | 153 (28.0%) | 74 (26.2%) | 79 (29.9%) | |
| | 6 | 5 (0.9%) | 1 (0.4%) | 4 (1.5%) | |
| | 7 | 2 (0.4%) | 1 (0.4%) | 1 (0.4%) | |
| Pupil (B) | | 244 (44.7%) | 112 (39.7%) | 132 (50.0%) | 0.016 |
| Rotterdam | | | | | 0.000 |
| | 1 | 20 (3.7%) | 9 (3.2%) | 11 (4.2%) | |
| | 2 | 157 (28.8%) | 79 (28.0%) | 78 (29.5%) | |
| | 3 | 157 (28.8%) | 63 (22.3%) | 94 (35.6%) | |
| | 4 | 76 (13.9%) | 41 (14.5%) | 35 (13.3%) | |
| | 5 | 93 (17.0%) | 55 (19.5%) | 38 (14.4%) | |
| | 6 | 43 (7.9%) | 35 (12.4%) | 8 (3.0%) | |
| First BS > 126 | | 460 (84.2%) | 248 (87.9%) | 212 (80.3%) | 0.018 |
| Midline shift | | 156 (28.6%) | 93 (33.0%) | 63 (23.9%) | 0.023 |
| SAH | | 206 (37.7%) | 117 (41.5%) | 89 (33.7%) | 0.064 |
| IVH | | 104 (19.0%) | 50 (17.7%) | 54 (20.5%) | 0.446 |
| EDH | | 121 (22.2%) | 66 (23.4%) | 55 (20.8%) | 0.536 |
| SDH | | 205 (37.5%) | 108 (38.3%) | 97 (36.7%) | 0.724 |
| ICH | | 162 (29.7%) | 78 (27.7%) | 84 (31.8%) | 0.303 |
| BSFX | | 196 (35.9%) | 87 (30.9%) | 109 (41.3%) | 0.012 |
| Pneumo | | 76 (13.9%) | 38 (13.5%) | 38 (14.4%) | 0.805 |

Abbreviations: B, brisk; BS, blood sugar; BSFX, base skull fracture; EDH, epidural hematoma; F, female; GSC, glasgow coma scale; ICH, intracerebral hemorrhage; IVH, intraventricular hemorrhage; mGSC, motor glasgow coma scale; Pneumo, pneumocephalus; SAH, subarachnoid hemorrhage; SDH, subdural hematoma.

**TABLE 2** | Machine learning models performance in predicting tracheostomy tube insertion need in patients with severe traumatic brain injury.

| Models | F1-score | Sensitivity | Specificity | PPV | NPV |
|---|---|---|---|---|---|
| LR | $0.51 \pm 0.09$ | $0.49 \pm 0.15$ | $0.64 \pm 0.13$ | $0.57 \pm 0.12$ | $0.59 \pm 0.09$ |
| RF | $0.57 \pm 0.11$ | $0.59 \pm 0.11$ | $0.58 \pm 0.07$ | $0.56 \pm 0.11$ | $0.61 \pm 0.07$ |
| GBT | $0.58 \pm 0.09$ | $0.58 \pm 0.09$ | $0.61 \pm 0.04$ | $0.58 \pm 0.09$ | $0.61 \pm 0.06$ |
| MLP | $0.60 \pm 0.09$ | $0.64 \pm 0.13$ | $0.55 \pm 0.15$ | $0.58 \pm 0.11$ | $0.63 \pm 0.07$ |

*Note:* Values are presented as mean ± standard error.
Abbreviations: GBT, gradient boosting machines; LR, logistic regression; MLP, multilayer perceptron; NPV, negative predictive value; PPV, positive predictive value; RF, random forest.

neurosurgeons commonly rely on factors such as the motor GCS, Rotterdam score, pupil reflex examination, and hematoma type to inform their predictions about patients who may eventually require tracheostomy. However, even after using various methods to fine-tune their parameters, our models that used these predictors derived from field attributes performed poorly. This suggests that the factors traditionally considered in clinical assessments may not be reliable predictors of the need for an

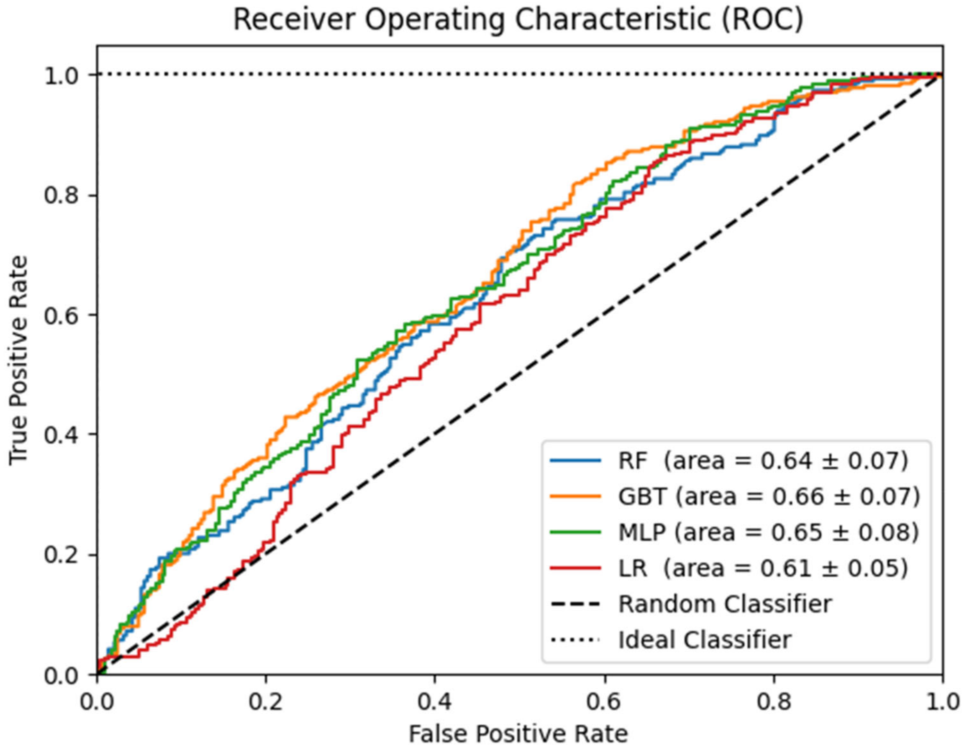


**FIGURE 1** | Area under receiver operating characteristic (ROC) curve (AUC) for prediction of the need for neurosurgical intervention. Values are presented as mean ± standard error. GBT, gradient boosting machines; LR, logistic regression; MLP, multilayer perceptron; RF, random forest.

early tracheostomy. The findings pose concerns about the efficacy of these factors and call for a critical rethinking of the predictive paradigms currently used in determining the need for tracheostomy in severe TBI cases.

Several recent studies have demonstrated the benefits of early tracheostomies (performed within 8 days after intubation) in severe brain injury cases [18, 19]. These studies have shown reduced mechanical ventilation duration, reduced ventilator-associated pneumonia, and decreased hospital and intensive care unit stays [3]. Besides its benefits for infectious complications and resource efficiency, studies have found a link between early tracheostomy and improved long-term outcomes [4].

Several studies aimed to identify predictors of the need for an early tracheostomy, typically taking into account factors such as age, GCS ≤ 8, and unreactive pupils [4]. It is worth noting, however, that these studies have rarely focused on using initial data collected in the emergency room, indicating a gap in understanding the immediate indicators available upon patient arrival. Despite the well-established importance of during-hospitalization variables in predicting the need for tracheostomy, there is a notable lack of research focusing on the critical early-stage information gathered in the emergency room setting. One study based on clinical and radiological findings at admission identified ten associated factors with the need for tracheostomy, including CRASH score, IMPACT score, SAPS II score, APACHE II score, age, revised trauma score, GCS, subdural hematoma, abnormal pupil response, and basal cistern collapse. The study concludes that these factors, assessed at admission, provide predictive insight into which adult patients with severe TBI may benefit from tracheostomy [20]. Another study revealed that admission characteristics significantly linked to tracheostomy included admission GCS, Marshall score, Injury Severity Score (ISS), end-stage renal disease, pneumothorax, hemothorax, chest tube, and lung injury score [21].

Shamim et al. aimed to investigate the predictability of tracheostomy requirement in patients with isolated severe TBI upon arrival at the emergency department. Utilizing a retrospective study design, they employed multivariate logistic regression analysis to identify predictive indicators. The findings demonstrated that in patients with isolated severe TBI, independent predictors of tracheostomy requirement included factors such as age (31–50 years), pre-existing comorbidities, delayed arrival at the emergency department exceeding 1.5 h, and abnormal pupil response on arrival [22]. However, these findings were validated in a small patient cohort of 98 patients, indicating the potential for predicting tracheostomy needs in patients with severe TBI upon emergency department admission. To enhance the robustness and generalizability of the results, additional validation through larger prospective studies is recommended.

Although many ML models have demonstrated commendable performance in predicting neurosurgical outcomes [23], the need for intervention [24], and various medical scenarios [25], our study represents an innovative effort to predict the need for tracheostomy in isolated severe TBI patients based on ML. Our model achieved a best AUC of 66%, suggesting suboptimal predictive accuracy. The limitations in predictive performance could be attributed to various factors, underscoring the complexity of predicting tracheostomy needs in isolated severe TBI

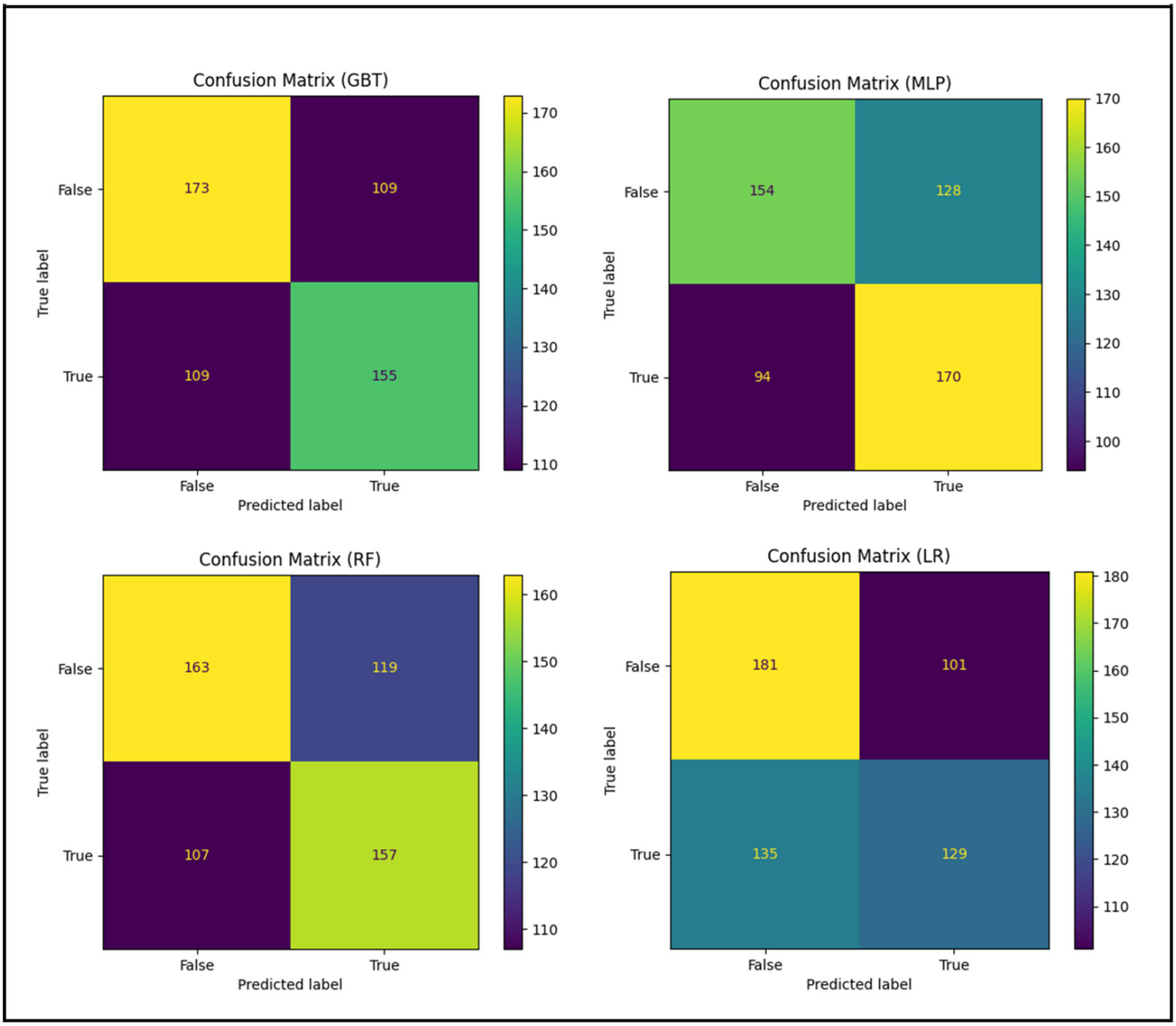


**FIGURE 2** | The confusion matrix of each model: The confusion matrix describes the performance of each model.

cases. One potential reason could be the inclusion of inaccurate or irrelevant field attributes as predictors in the data set. Though common variables such as age, GCS, Rotterdam score, pupil response, midline shift, and intracranial hematoma are conventionally considered predictors, it is plausible that these attributes may not truly reflect the complex nature of tracheostomy necessity. Other crucial variables or confounding factors that play a role in predicting tracheostomy need may not have been considered in the initial set of predictors. Failure to account for these variables could lead to an incomplete understanding of the predictive factors.

## 6 | Limitations and Further Research

The retrospective nature of the data set and its collection from a single tertiary center may limit the generalizability of the models. The data set's exclusivity to a particular center might introduce biases and fail to capture the diverse array of TBI cases seen in different healthcare settings.

Furthermore, the division of the data set into 70% for training and 30% for testing might have resulted in an insufficient amount of data for training robust models. A larger data set could potentially enhance the models' ability to learn and generalize patterns more effectively. Moving forward, addressing these limitations involves a critical reassessment of predictor selection in isolated severe TBI cases.

## 7 | Conclusion

Our study aimed to develop an ML-based model for predicting tracheostomy in isolated severe TBI patients. Despite employing commonly recognized predictors such as age, GCS, Rotterdam score, pupil response, first blood sugar, shift, and intracranial hematoma, the models' best performance was the AUC of 0.66. Our findings emphasize the complexity inherent in predicting tracheostomy necessity in isolated severe TBI patients and underscore the importance of ongoing research efforts to refine predictive models, ultimately contributing to more informed clinical decision-making in the management of these challenging cases. The findings of this study are a valuable starting point for the development of a predictive model and reassessment of factors considered in the clinical setting that may not be reliable predictors of the need for tracheostomies at admission.

### Author Contributions

**Adrina Habibzadeh:** conceptualization, investigation, writing – original draft, methodology, visualization, writing – review and editing, data curation, validation. **Sepehr Khademolhosseini:** visualization, validation, formal analysis, data curation, software, methodology. **Reza Taheri:** conceptualization, investigation, validation, supervision, project administration, writing – review and editing. **Amin Niakan:** conceptualization, investigation, resources, supervision. **Saeed Tayebi Khorami:** writing – review and editing. **Hadis Ghasemi:** writing – review and editing. **HosseinAli Khalili:** conceptualization, investigation, resources, supervision, project administration.


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### Ethics Statement

This study was performed after obtaining the ethics approval of Shiraz University of Medical Sciences.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

### Transparency Statement

The lead author Reza Taheri affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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