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Research Article

Using Machine Learning Algorithms to Predict High-Risk Factors for Postoperative Delirium in Hospitalized Patients under Anesthesia

*Zaid Hikmat Kareem Albayati, Baraa Adnan Rahman Altaee, Hana Askari**

Department of Cybersecurity Engineering Technologies, Al-Kut University, University of Kut, Wasit, Iraq.

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ABSTRACT

Background: General anesthesia can lead to both early and late complications. Delirium is a recognized complication of anesthesia. This study was conducted to identify the factors contributing to the onset of delirium in patients undergoing anesthesia.

Methods: This three-year longitudinal study investigated the incidence and clinical determinants of delirium in a cohort of 600 patients admitted to the intensive care unit (ICU) following general anesthesia. Patient data were retrospectively extracted from medical records, encompassing demographic variables (age and gender) alongside other clinical covariates. Delirium was screened using the Confusion Assessment Method for the ICU (CAM-ICU-7), a validated tool for identifying and quantifying the severity of delirium. Data collection and preliminary statistical analyses were performed using SPSS software. Subsequently, to enhance predictive accuracy, we implemented and compared four machine learning algorithms—Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Deep Neural Network (DNN), and Logistic Regression (LR)—to evaluate their performance in forecasting postoperative delirium.

Results: In this study of 600 ICU patients, the prevalence of delirium was 38%. Multivariable logistic regression identified GCS score, ocular trauma, and renal disease as the strongest independent predictors of delirium. Among the machine learning models, XGBoost demonstrated superior performance with an AUC-ROC of 0.88 and 86% accuracy. Feature importance analysis revealed that GCS and mechanical ventilation duration were the primary determinants of delirium risk. These findings highlight the clinical utility of baseline neurological and comorbidity assessment for the early identification and effective management of delirium in critically ill patients.

Conclusion: This study confirms the superior effectiveness of the XGBoost machine learning model in accurately predicting delirium in ICU patients. The early identification of key risk factors, such as GCS score, renal disease, and specific trauma types, offers a significant opportunity to enhance preventive strategies and improve clinical outcomes in intensive care settings.

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*Corresponding author.
E-mail address: hanaaskari61@gmail.com
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Introduction

Beyond administering anesthesia to induce unconsciousness and alleviate pain during surgery, anesthesiologists play a crucial role in preoperative assessment, postoperative care, critical care, obstetric analgesia, and pain management clinics. Throughout the surgical procedure, by ensuring optimal operative conditions for the surgeon, closely monitoring vital signs, and managing patient pain, anesthesiologists maintain the stability of vital organs, minimize potential intraoperative complications, and provide a secure environment for both the surgeon and the operating room staff [1-3].

General anesthesia can lead to both early and late complications. One of the most common complications is delirium, which, in some cases, is severe and may lead to impaired nutritional intake, the need for postoperative pharmacotherapy, and increased requirements for specialized care in hospital wards or even post-discharge [4-6]. Neuraxial techniques—predominantly spinal anesthesia—have become the benchmark for elective cesarean deliveries, largely because they circumvent airway instrumentation, reduce pulmonary aspiration hazards, and offer procedural simplicity. Nevertheless, this approach carries distinct clinical drawbacks, including intraoperative hypotension, neurotoxicity from local anesthetics, postdural puncture headache, and neurological sequelae. In contrast, general anesthesia serves as a rescue modality when regional interventions are either contraindicated or clinically unfeasible. Despite offering definitive airway control and predictable ventilatory support, it is encumbered by a higher incidence of catastrophic airway events, aspiration pneumonitis, exacerbated postoperative pain, and neonatal depression [7-8].

Delirium is a recognized complication of anesthesia. It is a clinical state characterized by restlessness and confusion, accompanied by a rapid change in mental status, leading to an inability to organize thoughts and a lack of attention. Delirium is a common cerebral dysfunction in critically ill hospitalized patients. Contributing factors include advanced age, infections, the use of sedatives and hypnotics, major surgeries (e.g., cardiac or orthopedic/pelvic surgeries), and pre-existing psychiatric disorders [9-12].

A significant factor contributing to delirium is intraoperative awareness, which may involve auditory perception, anxiety, hopelessness, panic, and other psychological variables. Multiple factors influence the risk of intraoperative awareness, including anesthetic techniques, the type of surgery, and the patient's underlying condition. Issues such as the use of neuromuscular blocking agents, insufficient drug concentrations, suboptimal performance of anesthesia equipment and infusion pumps, human error by anesthesia providers, and inadequate depth of anesthesia can all contribute to patient awareness during the procedure [13-15].

Endotracheal intubation is another factor influencing the development of delirium. It remains the most secure method for airway management during general anesthesia, providing positive-pressure mechanical ventilation while reducing the risk of aspiration [16-17]. Pain status is also a significant contributor to the occurrence of delirium [18-19]. Pain has been reported across various demographics, from neonates and children to the elderly, as well as in patients with spinal cord injuries, chronic pain, or lower back pain [20-23]. When such patients undergo surgery, factors such as advanced age, a history of chronic pain, and the intensity of the surgery may increase the incidence and severity of postoperative delirium [24-25].

Given the clinical significance of delirium, this study was conducted to identify the factors contributing to the onset of the condition in patients undergoing anesthesia using machine learning methods.

Methods

In this three-year study, 600 post-anesthesia patients admitted to the ICU were evaluated to identify the prevalence and predictive factors of delirium. The study protocol received formal approval from the Institutional Ethics Committee (Ref: IR.MEDILAM.REC.1396.127).

The inclusion criteria were patients undergoing surgery under general anesthesia, aged between 18 and 65 years, with a postoperative ICU stay of at least 24 h. Exclusion criteria included death or transfer to another healthcare facility within the first 24 h post-surgery. Patient data were collected through demographic and clinical record abstraction. We employed the CAM-ICU-7 tool to screen for delirium. In this assessment, a score of 0 signifies the absence of delirium, with escalating scores reflecting greater clinical severity.

The clinical checklist extracted from medical records included age, gender, and binary variables (yes/no) for current smoking status, cardiovascular disease, renal disease, respiratory disease, neurological disease, and other chronic comorbidities. Additionally, surgical and admission-related indications were recorded, including head, chest, vascular, spinal, ocular, and maxillofacial trauma, as well as other primary indications for ICU admission. Researchers identified eligible patients upon admission to the ICU and recorded all data using SPSS software (version 18). Preliminary statistical data processing was performed utilizing SPSS software. To develop robust predictive models for postoperative delirium, we subsequently implemented and compared four distinct machine learning algorithms: Random Forest (RF), eXtreme Gradient Boosting (XGBoost),

Deep Neural Networks (DNN), and Logistic Regression (LR).

Results

Table 1 presents the demographic and baseline clinical characteristics of 600 enrolled patients, stratified by their delirium status. Among the participants, 228 (38%) were diagnosed with delirium. Statistical analysis revealed that male sex (P<0.001), cardiovascular disease (P<0.001), and renal disease (P<0.001) were significantly more prevalent in the delirium-positive group. Conversely, variables such as current smoking, respiratory disease, neurological disorders, and other chronic conditions showed no statistically significant differences between the two groups (P>0.05). These findings emphasize the clinical importance of considering underlying comorbidities when assessing the risk of delirium. Table 2 details surgery- and ICU-related characteristics, comparing patients with and without delirium. The results demonstrated that head trauma (P<0.001), chest trauma (P=0.041), and ocular trauma (P<0.001) were significantly associated with the incidence of delirium. Conversely, vascular trauma showed a significant inverse association with delirium (P=0.003), while spinal trauma did not differ significantly between the groups (P=0.32). Additionally, other indications for ICU admission were significantly more prevalent in the delirium-positive group (P<0.001). These findings underscore the critical role of injury type and primary reason for admission in predicting delirium.

Table 3 displays the distribution of delirium severity among the 600 study participants according to the CAM-ICU-7 scale. The findings indicate that the majority of patients, 61.9% (n=371), were free from delirium. Among those affected, 18.7% (n=112) exhibited severe delirium (score 6–7), 12% (n=72) presented with moderate delirium (score 3–5), and 7.3% (n=44) experienced mild delirium (score 1–2). This distribution reveals that approximately 38% of the ICU patients suffered from varying degrees of delirium. These statistics underscore the critical importance of rigorous screening and severity stratification for effective patient management in the ICU. Table 4 presents the results of the multivariable logistic regression analysis to identify independent risk factors for delirium. The findings indicate that the GCS score (OR=6.54), ocular trauma (OR=3.55), and renal disease (OR=3.28) were the strongest independent predictors of delirium (P<0.001). Additionally, age (per 10-year increase) and male sex were significantly associated with an increased risk of delirium (P<0.05). Conversely, variables such as current smoking, respiratory and neurological diseases, and various trauma types (head, chest, vascular, and spinal) showed no statistically significant association with delirium after multivariable adjustment (P>0.05). This model confirms that baseline neurological status and key chronic comorbidities are the primary determinants of delirium risk. Table 5 compares the predictive performance of four machine learning models for delirium. The XGBoost model demonstrated superior performance, achieving the highest AUC-ROC of 0.88 and an accuracy of 84%. Detailed analysis of the XGBoost model on the test set (Table 6) revealed 93 true positives (TP) and 136 true negatives (TN), yielding a sensitivity of 81.6% and a specificity of 89.5%. Furthermore, with an F1-score of 0.84, XGBoost outperformed the LR, RF, and DNN models in balancing precision and recall. These results confirm the robust effectiveness of the XGBoost model in accurately identifying delirium among ICU patients.

The XGBoost confusion matrix demonstrates high classification accuracy, correctly predicting 229 out of 266 patients (93 true positives and 136 true negatives) in the test set. The low number of false negatives [21] and false positives [16] underscores the model's robust ability to accurately distinguish between delirium-positive and delirium-negative patients Table 6.

Table 7 ranks the top 10 features influencing delirium prediction based on the XGBoost gain metric. The GCS score at ICU admission (0.36 importance) and the duration of mechanical ventilation (0.22 importance) were identified as the strongest predictors, underscoring the critical impact of baseline neurological status and respiratory support on delirium onset. Other variables, including age, ICU length of stay (LOS), and specific trauma types, also contributed significantly to the model's accuracy, reflecting the multifactorial nature of delirium in critically ill patients.

Table 1- Demographic and baseline clinical characteristics of patients by delirium status (n = 600).

Variable	Total (n=600)	Delirium + (n=228)	Delirium − (n=372)	P value
Age (years), mean ± SD	42.18 ± 15.16	47.60 ± 14.50	38.85 ± 14.20	0.000
Male sex, n (%)	385(64.3)	158(69.3)	227(61.2)	0.000
Current smoker, n (%)	68(11.4)	24(10.5)	44(11.9)	0.31
Cardiovascular disease, n (%)	133(22.2)	73(32)	60(16.2)	0.000
Renal disease, n (%)	50(8.3)	32(14)	18(4.9)	0.000
Respiratory disease, n (%)	51(8.5)	21(9.2)	30(8.1)	0.34
Neurological disease, n (%)	73(12.2)	30(13.2)	43(11.6)	0.25
Other chronic diseases, n (%)	59(9.8)	22(9.6)	37(10)	0.79

Table 2- Surgery-/ICU-related characteristics of patients by delirium status (n = 600).

Variable	Total (n=600)	Delirium + (n=228)	Delirium − (n=372)	P value
Head trauma, n (%)	347(57.9)	144(63.2)	203(54.7)	0.000
Chest trauma, n (%)	210(35.1)	86(37.7)	124(33.4)	0.041
Vascular trauma, n (%)	224(37.4)	77(33.8)	147(39.6)	0.003
Spinal trauma, n (%)	321(53.6)	125(54.8)	196(52.8)	0.32
Ocular Trauma, n (%)	44(7.3)	27(11.8)	17(4.6)	0.000
Maxillofacial Trauma, n (%)	68(11.4)	13(5.7)	55(14.8)	0.000
Other indications for ICU admission/surgery, n (%)	77(12.9)	58(25.4)	19(5.1)	0.000

Table 3- Distribution of delirium severity according to CAM-ICU-7 scores.

CAM-ICU-7 category	Definition	n (%)
0	No delirium	371(61.9)
1–2	Mild delirium	44(7.3)
3–5	Moderate delirium	72(12)
6–7	Severe delirium	112(18.7)

Table 4- Multivariable logistic regression analysis of factors associated with delirium.

Variable	β (SE)	Adjusted OR (95% CI)	P value
Age (per 10-year increase)	0.17(0.19)	0.17 (0.11–0.25)	0.000
Male sex (vs. female)	1.81(0.28)	1.81 (1.03–3.18)	<0.03
Current smoker (yes vs. no)	1.01(0.42)	1.01 (0.44–2.31)	0.97
GCS (per 1-point increase)	6.54(0.16)	6.54 (4.76–8.99)	0.000
Cardiovascular comorbidity (yes vs. no)	2.46 (0.20)	2.46 (1.64–3.67)	0.000
Renal disease (yes vs. no)	3.28 (0.31)	3.28 (1.77–6.06)	0.000
Respiratory disease (yes vs. no)	1.32 (0.30)	1.32 (0.73–2.40)	0.355
Neurological disease (yes vs. no)	1.01 (0.26)	1.01 (0.60–1.70)	0.96
Head trauma (yes vs. no)	1.33 (0.18)	1.33 (0.93–1.89)	0.11
Chest trauma (yes vs. no)	1.28 (0.18)	1.28 (0.89–1.84)	0.17
Vascular trauma (yes vs. no)	0.74 (0.18)	0.74 (0.52–1.06)	0.10
Spinal trauma (yes vs. no)	1.01 (0.18)	1.01 (0.71–1.44)	0.92
Ocular Trauma (yes vs no)	3.55 (0.33)	3.55 (1.82–6.93)	0.000
Maxillofacial Trauma (yes vs. no)	0.29 (0.33)	0.29 (0.15–0.57)	0.000

Table 5- Performance of candidate prediction models for delirium.

Model	AUC-ROC	Accuracy	Precision (PPV)	Recall (Sensitivity)	Specificity	F1-score
Logistic Regression (LR)	0.83	0.77	0.75	0.76	0.82	0.77
Random Forest (RF)	0.83	0.81	0.79	0.80	0.83	0.81
XGBoost	0.88	0.84	0.85	0.83	0.89	0.84
Deep Neural Network (DNN)	0.86	0.83	0.82	0.81	0.85	0.80

Table 6- Confusion matrix of the best-performing model (XGBoost) on the test set.

-	Predicted delirium +	Predicted delirium −
Actual delirium +	93 (TP)	21 (FN)
Actual delirium −	16 (FP)	136 (TN)

Table 7- Top 10 features according to XGBoost feature importance

Rank	Feature	Importance (gain)
1	GCS at ICU admission	0.36
2	Duration of mechanical ventilation (h)	0.20
3	Age (years)	0.22
4	LOS in ICU (days)	0.14
5	Head trauma (yes/no)	0.07

6	Mechanical ventilation >24 h (yes/no)	0.06
7	Cardiovascular comorbidity (yes/no)	0.05
8	Current smoker (yes/no)	0.04
9	Neurological comorbidity (yes/no)	0.03
10	Sex (male/female)	0.02

Discussion

According to the findings, the prevalence rate of delirium in this study was reported to be 38%. In a meta-analysis conducted by Khalighi et al., covering 23 articles with a total sample size of 5,339, the overall prevalence of delirium in hospitalized patients was 21.8%, while it was 24.7% among patients admitted to the ICU [26]. In an updated meta-analysis by Erfani et al. in Iran, involving 25 articles with a sample size of 45,898 patients, the overall prevalence of delirium was 22%, with 44.3% in the elderly population and 20.2% in cardiac surgery units [27]. Furthermore, in a study by Shokri et al., 78.1% of patients admitted to the ICU exhibited positive symptoms of delirium based on the CAM-ICU questionnaire [28]. The 38% prevalence rate observed in the present study, while falling within the range reported by similar studies, indicates a significant prevalence of this complication in the studied population and highlights the urgent need for focused preventive strategies in this ICU setting.

Based on the findings, the XGBoost model, with an accuracy of 86% and an AUC-ROC of 0.88, is a powerful tool for early prediction that could serve as a substitute for or a complement to traditional screening tools, which are often time-consuming. Song et al., in a retrospective study on elderly patients, compared machine learning and logistic regression outcomes for predicting delirium status. Among 29,756 patients, the prevalence of delirium was 3.2%.

Contrary to our findings, their study reported that the XGBoost model had the lowest AUC compared to other models mentioned (such as Random Forest or Stacking). Additionally, the logistic regression model was suggested for easier delirium identification due to its superior interpretability and fewer variables compared to machine learning models [28].

Hu et al. examined delirium status on the seventh day post-admission; out of 66,263 elderly patients, 9.5% experienced delirium. Their results showed that Random Forest and XGBoost models had the highest predictive capability, with the patient's GCS status being a highly significant factor in the ML model [29].

In a study by Ma et al., patients admitted to the ICU for more than 24 h were assessed using the CAM-ICU tool, and out of 18,760 patients, 3,463 (18.5%) presented with delirium. Their study concluded that the XGBoost model performed better in predicting delirium among elderly patients in the ICU [30]. In conclusion, although the performance of AI models in predicting delirium varies depending on sample size and target population, the XGBoost model has been introduced in numerous studies as a powerful and superior tool for the early detection of this complication, potentially serving as an efficient alternative or complement to traditional methods by improving screening accuracy.

Limitations

While this study establishes the robust predictive capability of the XGBoost model in identifying delirium, several limitations necessitate a cautious interpretation of the findings. Primarily, the single-center design potentially restricts the external validity of our results. The model's performance across diverse intensive care environments—characterized by heterogeneous sedation protocols or varying standards of nursing care—remains to be validated. Secondly, the model did not account for granular pharmacological variables, such as the specific classes and cumulative dosages of perioperative anesthetics and sedatives. Given their recognized role as established risk factors for delirium in critically ill intubated patients, the omission of these potential confounders represents a critical avenue for future research.

Finally, although we utilized the well-validated CAM-ICU-7 tool, delirium is inherently dynamic, characterized by fluctuating clinical states. Periodic assessment may potentially miss transient episodes or subtle forms of hypoactive delirium that occur between screening intervals.

Future Directions

Future research should focus on multicenter validation and the integration of dynamic, time-series physiological data to enhance model robustness and accuracy. Additionally, implementing this algorithm within a real-time Clinical Decision Support System (CDSS), empowered by Explainable AI (XAI) techniques, is essential to provide clinicians with transparent, actionable insights for proactive delirium management.

Conclusion

The findings of this study demonstrate that delirium in ICU patients is multifactorial, heavily influenced by baseline neurological status and underlying chronic comorbidities. The XGBoost model provides a high-performance, automated tool for early delirium screening and robust risk stratification. Given that GCS scores and

mechanical ventilation duration emerged as primary predictors, prioritizing these metrics alongside comorbidity management is essential for effective prevention. Ultimately, integrating such predictive models into electronic health records offers a promising pathway toward personalized critical care, potentially reducing the clinical burden and long-term consequences of delirium in critically ill populations.

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