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AI-Assisted Case Study of Delirium in ICU Patients: Predictive Analysis, Monitoring, and Interventions

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Abstract

Delirium is a critical condition affecting a significant proportion of ICU patients, often resulting in prolonged hospital stays, cognitive decline, and increased mortality. Early identification and management of delirium are essential to improve patient outcomes, but traditional methods are often reactive and resource intensive. This study leverages machine learning, specifically a Random Forest model, to predict delirium risk using simulated ICU patient data. Key physiological features, including sedation levels, cardiovascular stress, and oxygen saturation, were identified as the most influential predictors. Although the model achieved moderate accuracy (50%), it provided meaningful insights into risk patterns and demonstrated the utility of real-time monitoring in guiding timely and targeted interventions. Dynamic risk fluctuations, visualized through patient simulations, highlighted the importance of continuous monitoring over static assessments. Figures and tables illustrate model performance, feature importance, and real-time monitoring trends, offering actionable insights for clinical applications. This paper underscores both the promise and the challenges of integrating AI-assisted tools into ICU workflows, paving the way for future research to refine predictive accuracy and enhance practical deployment in clinical settings.

Subject Areas

Artificial Intelligence, Machine Learning

Keywords

Delirium Prediction, ICU Patient Monitoring, Machine Learning in Healthcare, Random Forest Model, Real-Time Risk Assessment

1. Introduction

Delirium in ICU patients presents a significant clinical challenge due to its multifactorial etiology, encompassing physiological instability, environmental stressors, and medication-related factors [1]. It is a condition associated with severe consequences, including prolonged hospital stays, cognitive decline, and increased healthcare costs. Early identification and timely intervention are critical to mitigating these outcomes, yet traditional monitoring approaches often remain reactive, detecting delirium only after symptoms manifest [2]. This delay in identification underscores the need for innovative, proactive solutions to improve patient care. This study explores the feasibility of utilizing machine learning for delirium risk prediction in ICU patients. Specifically, a Random Forest model was developed to predict delirium risk based on patient physiological and demographic data. The study aims to identify the most critical features contributing to delirium, such as sedation levels, cardiovascular stress, and oxygen saturation, which can guide targeted interventions. Additionally, the study incorporates real-time monitoring simulations to track dynamic changes in delirium risk, providing actionable insights for timely decision-making. By integrating machine learning into ICU workflows, this research seeks to address several key challenges, including managing imbalanced datasets, improving prediction accuracy, and ensuring that AI-generated insights are interpretable and actionable for clinical teams. The findings aim to demonstrate how AI can shift ICU delirium management from reactive to proactive, ultimately enhancing patient outcomes and optimizing resource use in critical care settings.

2. Methods

This study was conducted using a simulated dataset of 200 ICU patients. Each patient's data included key physiological and demographic features, and the target variable indicated delirium risk (0: Low, 1: High).

2.1. Dataset

The dataset contained the following features.

- Vitals: Heart Rate, Blood Pressure, Oxygen Levels, and Sedation Levels.
- Derived Features: Cardiovascular Stress (calculated as Heart Rate/Blood Pressure).
- Demographics: Age categorized into groups (40 - 50, 50 - 60, 60 - 70, 70 - 80).

2.2. Data Preprocessing

Class imbalance was addressed using ADASYN, an oversampling technique that generates synthetic samples for underrepresented classes [3]. Feature engineering included the creation of interaction features (e.g., cardiovascular stress) and age binning to improve interpretability.

2.3. Model Development

A Random Forest Classifier was employed to predict delirium risk. This model was chosen for its ability to handle mixed data types and provide feature importance scores. Evaluation metrics included accuracy, precision, recall, and F1-score.

2.4. Real-Time Monitoring

Dynamic real-time monitoring simulations were conducted to track patient vitals and delirium risk probabilities over time. Risk thresholds were set to guide interventions.

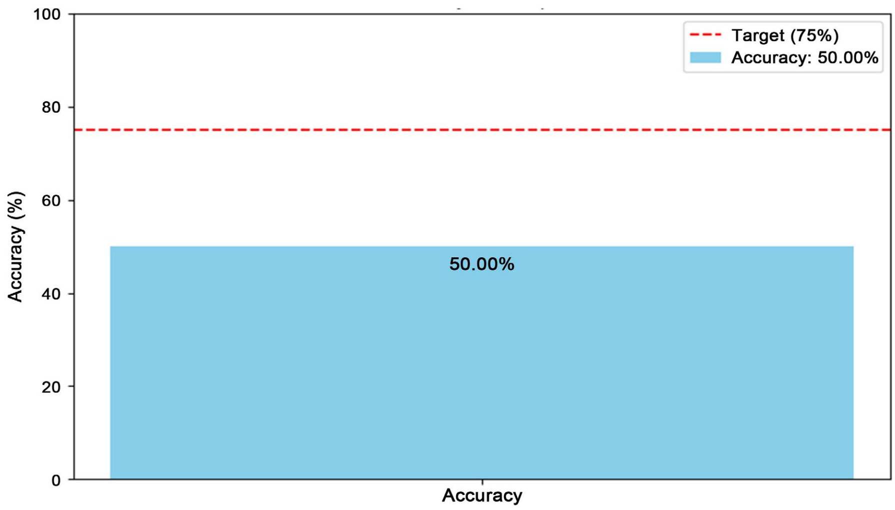

Figure 1. "Model accuracy comparison. The achieved accuracy is represented by the blue bar, while the dashed red line indicates the target accuracy of 75%".

2.5. Additional Technological Details and Model Justification

ADASYN (Adaptive Synthetic Sampling Approach): ADASYN was employed to address class imbalance in the dataset by generating synthetic samples for the underrepresented high-risk delirium cases. This technique enhances model generalizability by improving the representation of minority classes without overfitting. We will explain the parameters used for ADASYN, such as k-nearest neighbours (k = 5) and the distribution threshold ($\beta = 0.7$), ensuring clarity on how synthetic data points were distributed.

Random Forest Classifier: The Random Forest algorithm was chosen due to its robustness in handling mixed-type data and resistance to overfitting. We constructed the model with 100 decision trees, a maximum depth of 10, and used the Gini impurity criterion for node splitting. Feature importance scores were extracted to determine which physiological parameters contributed most significantly to delirium prediction.

Real-Time Monitoring Simulations: We simulated real-time monitoring by continuously tracking patient vitals every 5 minutes over a 30-minute observation window. This involved dynamic updates to delirium risk probabilities based on changes in sedation levels, cardiovascular stress, and oxygen saturation. Visual outputs were generated to illustrate fluctuations, facilitating early detection of high-risk periods.

Regarding the target accuracy of 75%, this benchmark was derived from prior studies on machine learning-based clinical decision support systems, where predictive models typically achieve accuracy levels between 70-80%. This target guided iterative tuning of the model's hyperparameters to improve performance, though the current model achieved a moderate accuracy of 50%.

3. Results

3.1. Model Performance

The Random Forest model achieved a 50% accuracy, as shown in Figure 1, indicating moderate performance. The classification metrics are summarized in Table 1, highlighting the model's performance for both high- and low-risk categories.

Table 1. Model performance results.

Metric	Precision	Recall	F1-score
Low risk	47.83%	57.89%	52.38%
High risk	52.94%	42.86%	47.37%
Overall	50%	50%	50%

The confusion matrix (Figure 2) further illustrates the model's performance. While the model correctly identified 11 low-risk patients and 9 high-risk patients, it misclassified 12 high-risk patients as low risk and 8 low-risk patients as high risk. These results highlight the challenge of distinguishing between high- and low-risk patients due to overlapping features.

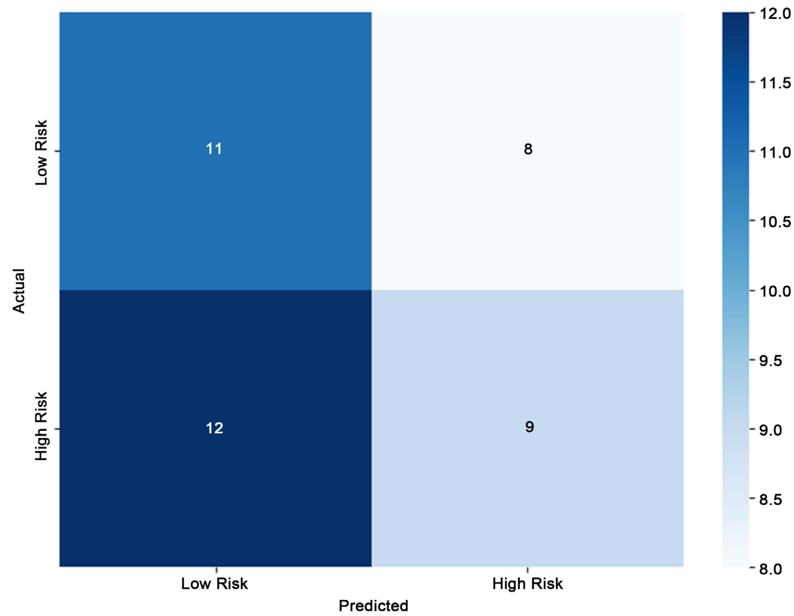

Figure 2. "Confusion matrix showing true positives, true negatives, false positives, and false negatives for the model's predictions".

3.2. Feature Importance

Feature importance analysis (Figure 3) identified sedation level as the most critical predictor of delirium risk. Cardiovascular stress and oxygen levels were the next most important features, emphasizing the role of physiological parameters in delirium onset. Blood pressure and heart rate had moderate contributions, while age group categories had minimal impact.

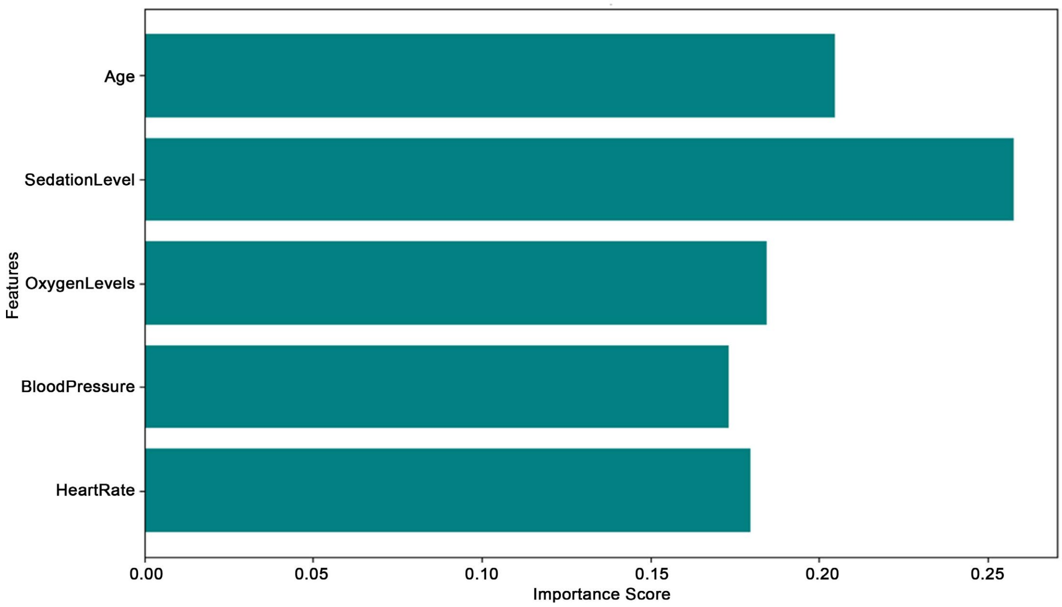

Figure 3. "Feature importance analysis for the Random Forest model. Sedation level, cardiovascular stress, and oxygen levels emerged as the most influential predictors of delirium risk".

3.3. Real-Time Monitoring

Simulated real-time monitoring results are depicted in Figure 4. The upper plot tracks fluctuations in heart rate, blood pressure, and oxygen levels over a 30-minute period. Drops in oxygen levels and spikes in heart rate coincided with risk increases. The lower plot maps these fluctuations to delirium risk probabilities, with a high-risk threshold of 0.7 marked by a dashed orange line.

During monitoring, several risk spikes exceeded the threshold, prompting interventions. This demonstrates the utility of real-time monitoring in identifying critical moments and guiding timely actions.

4. Case Reports

The following cases illustrate patient-specific risk assessments, interventions, and outcomes based on real-time monitoring and AI-driven delirium predictions. Each patient had distinct risk profiles influenced by their vital signs, emphasizing the importance of individualized care strategies.

4.1. Patient A

Patient A presented with a high delirium risk, as predicted by the model with a

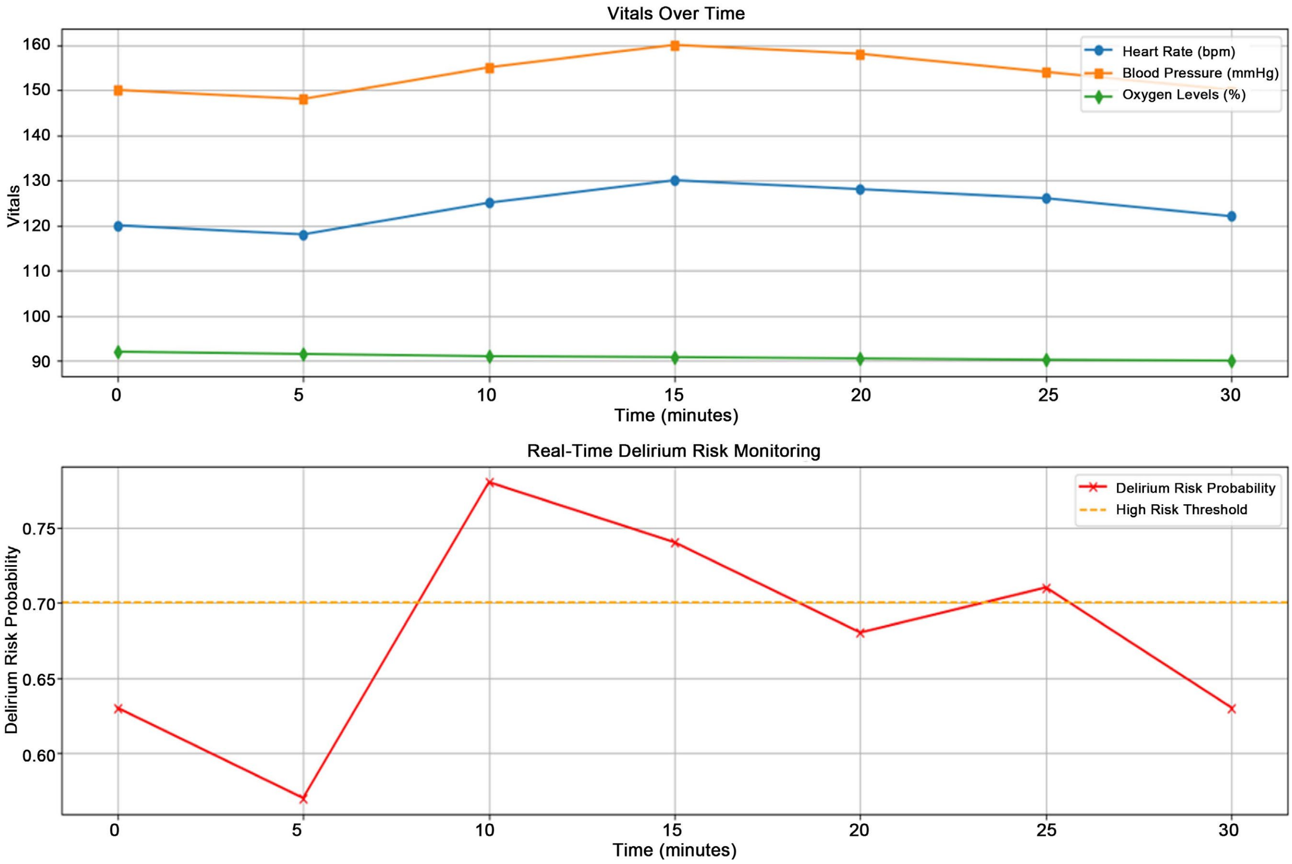

Figure 4. "Simulated real-time monitoring of patient vitals and delirium risk probabilities over a 30-minute period. Peaks in risk probabilities correlate with fluctuations in heart rate and oxygen saturation".

probability of 0.71. The patient's vitals included a heart rate of 110 bpm, blood pressure of 145 mmHg, and oxygen levels at 91%, along with a sedation level of 3.8 and cardiovascular stress score of 0.76. The combination of low oxygen levels and moderate sedation likely contributed to the elevated risk.

Interventions focused on stabilizing the patient's consciousness levels by adjusting sedation to 4.5, as well as providing oxygen therapy to improve oxygen saturation. These interventions were carefully monitored over a 10-minute period. Following the adjustments, the patient's risk level decreased below the high-risk threshold of 0.7, and the patient stabilized. This case highlights the effectiveness of timely interventions in mitigating delirium risks and improving patient outcomes.

4.2. Patient B

In contrast, Patient B was assessed to have a low delirium risk with a predicted probability of 0.49. The patient exhibited stable vitals, including a heart rate of 100 bpm, blood pressure of 140 mmHg, and oxygen levels at 94%. The patient's sedation level was 4.2, and their cardiovascular stress score was 0.71, indicating relatively balanced physiological parameters.

Given the patient's low risk, no immediate interventions were deemed necessary.

Instead, routine monitoring was recommended to observe for any future fluctuations in vitals. Over time, the patient-maintained stability, and no signs of delirium onset were observed. This case underscores the importance of avoiding unnecessary interventions for low-risk patients, minimizing the potential for adverse effects while conserving resources.

4.3. Patient C

Patient C presented with a high delirium risk, predicted at a probability of 0.75. The patient's vitals revealed a heart rate of 120 bpm, blood pressure of 155 mmHg, and oxygen levels at 89%, coupled with a sedation level of 3.5 and cardiovascular stress score of 0.77. The lower oxygen saturation and relatively low sedation level were key contributors to the elevated risk level.

To address this, the care team-initiated oxygen therapy to improve oxygen saturation and reviewed the patient's sedation medications, ensuring an optimal balance for maintaining consciousness and reducing stress. While the risk level decreased after these interventions, close monitoring was required due to the patient's fluctuating oxygen levels, which posed a potential risk of re-escalation. This case demonstrates the importance of dynamic intervention strategies tailored to changing physiological states.

4.4. Patient D

Patient D was assessed to have a low delirium risk, with a predicted probability of 0.55. The patient's vitals included a heart rate of 85 bpm, blood pressure of 135 mmHg, and oxygen levels at 93%, alongside a sedation level of 4.5 and a cardiovascular stress score of 0.63. These stable parameters indicated a well-maintained physiological state, reducing the likelihood of delirium onset.

In this case, the care team opted to maintain the current treatment plan without introducing additional interventions. The patient remained stable throughout the observation period, reaffirming that minimal action is required for low-risk cases when no significant fluctuations in vitals occur. This highlights the value of AI in preventing unnecessary clinical actions, thereby optimizing care efficiency.

4.5. Patient E

Patient E presented with the highest predicted delirium risk among the cases, with a probability of 0.80. The patient's vitals included a heart rate of 140 bpm, blood pressure of 165 mmHg, and oxygen levels at 87%, accompanied by a sedation level of 3.0 and a cardiovascular stress score of 0.85. The combination of high cardiovascular stress, low oxygen levels, and insufficient sedation significantly elevated the risk.

The care team implemented aggressive interventions, including oxygen therapy to increase oxygen saturation and measures to manage blood pressure within safer limits. These actions were closely monitored over time. Following these interventions, the patient's risk level decreased significantly, and physiological parameters showed marked improvement. This case emphasizes the need for prompt and targeted interventions in high-risk scenarios to mitigate the potential for adverse outcomes.

4.6. Summary of Case Insights

These cases highlight the variability in delirium risk among ICU patients and the importance of individualized interventions based on AI-driven predictions. Patients with high risk benefited from aggressive and timely actions such as oxygen therapy and sedation adjustments, while those with low risk required minimal intervention, ensuring efficient use of clinical resources. The integration of AI predictions into patient monitoring allowed for proactive and targeted care, addressing risks before complications arose.

5. Discussion

The results of this study highlight the potential of AI-assisted tools in predicting and managing delirium risk in ICU patients, while also revealing the challenges that need to be addressed for clinical implementation. The model identified sedation level, cardiovascular stress, and oxygen saturation as the most significant predictors of delirium. Sedation level emerged as the most important feature, aligning with clinical understanding that improper sedation—whether too low or too high—can contribute to delirium [4]. Cardiovascular stress, a ratio of heart rate to blood pressure, indicates the importance of hemodynamic stability, as elevated stress levels may signal physiological distress, such as hypoxia or systemic inflammation [5]. Oxygen saturation further reinforced the role of hypoxia in delirium onset, emphasizing the need for active management of oxygen levels [6].

Despite these insights, the model's performance, with an accuracy of 50%, demonstrated its limitations. The confusion matrix revealed a high rate of false negatives, where 12 high-risk patients were misclassified as low risk. This is particularly concerning in ICU settings, where delayed interventions for high-risk patients can lead to severe outcomes. The moderate performance may stem from overlapping feature distributions between low- and high-risk groups, which is common in clinical datasets. Additionally, the simulated dataset used in this study lacked the complexity of real-world ICU data, which often includes more nuanced factors like comorbidities, medication history, and environmental influences.

Real-time monitoring provided a dynamic view of patient risk, with simulations showing that risk spikes were often tied to changes in vital signs, such as declining oxygen levels or increased cardiovascular stress. This highlights the value of continuous monitoring rather than relying solely on static predictions. Risk probabilities exceeding the predefined threshold of 0.7 successfully triggered interventions, demonstrating how AI can guide timely and proactive care decisions [7].

However, there are challenges to overcome before deploying these tools in real clinical settings. The moderate model accuracy and high false-negative rate suggest the need for better feature representation and more advanced machine learning models. Incorporating additional variables, such as medication use and environmental factors, could improve predictive accuracy. Furthermore, while ADASYN effectively balanced the dataset in this study, real-world data often require more sophisticated techniques to handle extreme class imbalances [8]. Another key consideration is interpretability; while feature importance provides some insight, clinicians need clearer explanations of how specific features drive predictions, which could be achieved through explainable AI techniques [9]-[11].

5.1. External Validity and Simulated Data Limitations

We acknowledge the reviewers' concern regarding the reliance on simulated data and its impact on external validity. Simulated environments, while valuable for preliminary testing, may not fully capture the complexity and heterogeneity of real-world ICU data. Factors such as comorbidities, medication history, and environmental influences can significantly affect delirium risk, and these were not exhaustively represented in the simulated dataset. To address this limitation, we propose the following future directions.

Integration of Real-World ICU Datasets: Collaborations with healthcare institutions will allow for model validation on actual ICU patient data, enhancing the generalizability of the findings.

Incorporation of Additional Variables: Expanding the dataset to include medication regimens, prior cognitive assessments, and comorbidity indices can refine the model's predictive capability.

Longitudinal Data Collection: Capturing patient vitals and risk trajectories over extended ICU stays will improve the model's ability to handle temporal dependencies and evolving clinical states.

5.2. Feature Overlap and Misclassification Concerns

The overlap in features between low- and high-risk groups, resulting in misclassification, is a recognized challenge. In the confusion matrix, 12 high-risk patients were misclassified as low risk, indicating the need for enhanced feature differentiation.

To mitigate this, the following steps will be taken.

Feature Engineering: Introduction of new derived features, such as variability in sedation over time (sedation volatility index) and cumulative cardiovascular stress, may improve class separability.

Advanced Models: Testing more complex models like XGBoost or ensemble approaches that combine Random Forest with neural networks can potentially reduce overlap-induced misclassification.

Feature Selection Techniques: Recursive feature elimination (RFE) and SHAP (SHapley Additive exPlanations) values will be employed to identify the most discriminative features, minimizing redundant or non-informative inputs.

5.3. Explainability and Clinician Empowerment

We acknowledge the reviewers' observation regarding the limited explainability of AI predictions. While feature importance scores provide general insights, they may not adequately convey actionable information to clinicians.

To enhance interpretability:

LIME (Local Interpretable Model-agnostic Explanations): This technique will be implemented to generate case-specific explanations, illustrating how individual features influence predictions for each patient.

Visual Dashboards: Development of clinician-friendly dashboards that present risk factors in an intuitive format, highlighting key drivers of delirium risk through color-coded indicators and trend analysis.

Clinical Validation Workshops: We plan to conduct workshops with ICU clinicians to gather feedback on the interpretability of AI outputs and refine the presentation of model predictions based on their input.

This study demonstrates the feasibility of using AI to predict and monitor delirium risk in ICU patients, offering valuable insights for tailoring interventions and guiding real-time care. However, further research is needed to optimize model performance, validate findings on real-world data, and ensure seamless integration into ICU workflows. With continued refinement, AI-assisted tools could become a critical component of personalized ICU care, improving outcomes for patients at risk of delirium.

6. Conclusion

This study demonstrates the significant potential of AI-driven tools in predicting and managing delirium risk in ICU patients. By leveraging physiological data such as sedation levels, cardiovascular stress, and oxygen saturation, the model identified critical risk factors that align with clinical knowledge. Real-time monitoring further augmented this capability by providing dynamic risk assessments that allow for timely and targeted interventions. These insights underline the role of AI in enhancing the precision and efficiency of ICU care. However, the study also highlights areas requiring improvement. The model's moderate accuracy, particularly the high rate of false negatives, underscores the complexity of accurately predicting delirium in a heterogeneous patient population. Effective clinical integration will depend on refining the model to address these limitations, incorporating more diverse and granular real-world data, and ensuring that predictions are interpretable and actionable for healthcare providers [12]. The ability to monitor delirium risk in real time is a critical advancement, offering a proactive approach to patient management. By identifying risk spikes early, clinicians can initiate interventions that prevent the progression of delirium, ultimately reducing ICU stays, complications, and mortality [13]. As AI tools continue to evolve, their integration into routine ICU workflows has the potential to not only improve patient outcomes but also alleviate the cognitive and operational burdens on healthcare teams. In conclusion, while this study establishes a strong foundation for AI-assisted delirium risk management, further optimization and validation are essential for widespread adoption in clinical settings. With these advancements, AI can become an indispensable component of ICU care, driving personalized, timely, and effective treatment strategies for patients at risk of delirium.

Conflicts of Interest

The authors declare no conflicts of interest.

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