RESEARCH PAPER

Artificial intelligence and machine learning for predicting intracranial pressure crises in TBI patients.

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ABSTRACT
Traumatic brain injury (TBI) is still the most common cause of death and long-term disability due to nervous system damage in the world. One of the main reasons for this is the drastic increase in intracranial pressure (ICP) in cases of moderate to severe TBI. The traditional method of controlling ICP involves continuous monitoring of pre-established threshold values and administering treatments only when necessary. However, this strategy often fails to grasp the intricate, non-linear and time-related physiological changes that eventually lead to increased intracranial pressure. In this work, an AI-based approach together with a machine learning technique is proposed for the crisis detection of ICP in TBI patients, which would be entirely based on high-resolution physiological data and clinical variables. The research was retrospective and observational, and it was performed in MIMIC-III and MIMIC-IV patients' ICU databases. It consisted of adult ICU patients with TBI that were subjected to invasive ICP monitoring. Continuous ICP and blood pressure waveforms were combined with demographic, neurological, and clinical intervention data. ICP crisis was determined by a rise of ≥20–22 mmHg for at least five minutes, and a labeling technique involving sliding time-window was applied. A variety of the supervised ML models such as logistic regression, random forests, support vector machines, gradient boosting, RNNs, and LSTMs, etc., were created and tested through patient-wise data division to ensure no mixing of information occurs. The performance of the models was evaluated using clinically significant measures like area under the receiver operating characteristic curve (AUROC), sensitivity, specificity, precision, recall, and early warning time. Classic ML models showed strong predictive power on developed features, while LSTM-based models got better results by recognizing long term time dependencies in raw waveform data which made earlier and more accurate detection of coming ICP crises possible. The results indicate that the use of AI in predictive modeling can greatly improve the early risk assessment and the support of proactive interventions in neurocritical care. This framework highlights the potential of machine learning based decision support systems to transition ICP management from reactive threshold-based approaches toward anticipatory, personalized, and precision-guided care for patients with traumatic brain injury

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INTRODUCTION
Worldwide, Traumatic brain injury (TBI) is still the foremost reason for death and permanent neurological disability in the society, especially in young adults and the economically active groups. The development of intracranial pressure (ICP) crises, that is, episodes of intracranial hypertension that lead to less blood flow to the brain, worsen brain injury, and, hence, more death and suffering, is a major factor determining the outcome in moderate to severe TBI cases. Although neurocritical care has improved, the timely prediction and prevention of ICP crises remain major difficulties in the clinic as a result of the complicated, changing, and individual-based pathophysiology of brain injury[1].
Moreover, the conventional ICP management strategies depend on the monitoring that is based on thresholds and the subsequent interventions. These interventions, however, are not initiated until after the ICP has already been elevated to a dangerous level. The approaches mentioned may not be able to detect the subtle temporal patterns or nonlinear interactions that are among physiological variables that lead to the occurrence of life-threatening ICP events. There has been a significant upsurge in the interest on the part of the researchers and clinicians in the application of Artificial

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Intelligence (AI) and Machine Learning (ML) techniques which will facilitate the earlier, data-driven prediction of ICP crises and, thus, the support of proactive, personalized neurocritical care[2-3].
Researchers in recent times have shown that ML models are able to predict intracranial hypertension and ICP-related outcomes by means of physiological data and clinical variables of very high resolution as well as monitoring streams from neurointensive care. Supervised learning algorithms like logistic regression, random forests, support vector machines, gradient boosting, and neural networks have been used to predict ICP crises hours in advance, assess TBI severity, and decide discharge outcomes based on ICP trends. The more contemporary architectures like recurrent neural networks (RNNs) and long short-term memory (LSTM) models have given especially good performance in capturing the temporal dependencies that are characteristic of ICP waveform data and thus allowing real-time risk prediction in neurointensive care settings[4].
Single center and multicenter studies have all pointed to the same conclusion that ML based models are more capable than traditional rule-based or static statistical methods in identifying patients at high risk of having ICP elevated to harmful levels during the acute phase of TBI. Additionally, externally validated models have provided evidence of good generalizability, thus supporting their potential integration into clinical practice. Reviews of ML methods for ICP prediction have shown that there is always an improvement in the early warning capability, more so when multimodal data consisting of ICP, arterial blood pressure, cerebral perfusion pressure, and demographic and injury related variables are used together[5-7].
The advancements that have been made have not removed the challenges in model interpretability, data heterogeneity, and clinical adoption. The process of making the incorporation of AI-driven ICP prediction tools into clinical decision-making systems that are safe and effective would need to include steps like transparency, robustness across institutions, and real world clinical workflows alignment. The increasing number of studies supporting the use of AI and ML in the transformation of managing ICP through the transition from reactive treatment to anticipatory and precision-guided neurocritical care is overwhelming[8]. This research is a continuation of previous machine learning frameworks for ICP prediction, with the intent of further enhancing the accuracy and relevance of the predictions in clinical practice for patients suffering from traumatic brain injury through the use of advanced data-driven modeling techniques[9].

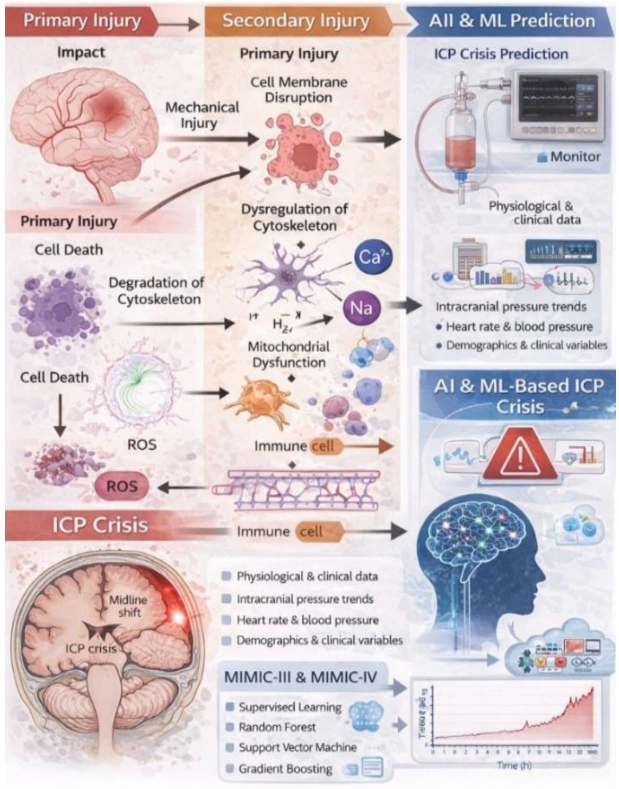

Figure 1. Machine learning approaches for intracranial pressure crisis prediction in literature-based review

Prior studies related to the use of AI and ML algorithms for ICP crises prediction in traumatic brain injury patients are summed up in Figure 1. It shows the movement from traditional threshold-based ICP monitoring to data-driven predictive models which make use of high-resolution physiological waveforms and clinical variables. The literature points out the predominance of machine learning and deep learning models, especially recurrent architectures, in capturing nonlinear and temporal physiological patterns that precede ICP crises. This, in turn, allows for earlier intervention and better results in neurocritical care.

LITERATURE REVIEW

Traumatic brain injury (TBI) still accounts for a huge chunk of the cases of disability and death globally, with the occurrence of secondary brain injury mainly determining patient outcomes. Out of the various secondary brain injuries, intracranial hypertension (ICH) and intracranial pressure (ICP) crises are the most common ones and very much linked to a wide range of unfortunate events like cerebral ischemia, brain herniation, prolonged intensive care stays, and poor neurological recovery. The traditional approach to ICP management is based on the monitoring of certain thresholds and the judgment of the doctor, which might not be able to predict rapid physiological deterioration. AI and machine learning (ML), in this regard, are viewed as the best coming tools for the early prediction of ICP crises and thus leading the way to proactive and personalized neurocritical care[10-11].

One of the earliest attempts in this direction was the work titled "Prediction of intracranial pressure crises after severe traumatic brain injury using machine learning algorithms", which showed that ML models could attain better levels of accuracy than traditional statistical approaches when it comes to the detection of imminent ICP elevations. By analyzing high-frequency physiological data that encompassed ICP waveforms, cerebral perfusion pressure, and systemic vital signs, the models were able to detect the complex nonlinear interactions which took place prior to ICP crises. The application of machine learning has been credited with the upward trend in sensitivity concerning the prediction of ICP thresholds that went beyond critical levels, thus ML's influence on early intervention strategies for severe TBI patients has been emphasized[12-16].
Besides that, the Prediction of Life-Threatening Intracranial Hypertension During the Acute Phase of Traumatic Brain Injury Using Machine Learning study was conducted in a very acute neurocritical care phase where the rapid rise of ICP posed immediate dangers. The study not only shorted the prediction windows to a few minutes but also proved that the ML models could detect the threatening condition of intracranial hypertension even two to three hours before it was clinically noticed. The features of early warning mentioned above proved so effective that they were used in making decisions regarding hyperosmolar therapy, sedation, and even surgical intervention[17-18].
The machine learning technology has been additionally applied in the analysis of severity and prognosis with the help of ICP-derived features in the field of crisis detection. The research paper 'Predicting the Severity and Discharge Prognosis of Traumatic Brain Injury Based on Intracranial Pressure Data Using Machine Learning Algorithms' demonstrated that incorporating ICP trends, variability measures, and pressure burden indices could facilitate more accurate predictions for discharge outcomes compared to simply considering isolated mean ICP values. Furthermore, the results supported the view that ML interpreted dynamic ICP patterns yield more prognostic information than the static thresholds used less[19].
The Development and External Validation of a Machine Learning Model for the Early Prediction of Doses of Harmful Intracranial Pressure in Patients with Severe Traumatic Brain Injury not only provided a complementary view to the findings but also underscored the importance of external validation as a factor in the development of the ML models. The authors illustrated that multicenter dataset-trained ML models retained the same level of predictive performance across different institutions, thus eliminating a major disadvantage of early single-center studies and facilitating the acceptance of ML in wider areas of clinical practice[20-23].
Temporal dependency is considered as one of the major features characterizing ICP, thus this led to the adoption of recurrent neural networks (RNNs) for the research. In A Recurrent Machine Learning Model Predicts Intracranial Hypertension in Neurointensive Care Patients, the sequential deep learning architectures were able to successfully imitate time-series physiological data, thus making it possible to continuously assess the risk. This method not only caused the detection of intracranial hypertension events to be faster but also proved to be appropriate for real-time bedside decision support systems[24].
There was related research that although it was devoted to hemodynamic instability, it definitely pointed out the strength of real-time ML systems in the context of TBI care, for example, A Machine Learning Approach for Predicting Real-time Risk of Intraoperative Hypotension in Traumatic Brain Injury. Furthermore, this study was not exclusively focusing on ICP but on the contrary, it pointed out how continuous ML driven risk stratification could be applied to perioperative and intensive care settings which strengthened the case for similar systems for ICP crisis prediction[25-27].
This research, Machine Learning Approaches to Intracranial Pressure Prediction in Patients with Traumatic Brain Injury: A Systematic Review, presents a complete picture of the situation by evaluating different ML techniques like logistic regression, tree-based models, support vector machines, and deep learning architectures. The paper mentioned that the ML models are consistently better than the traditional predictive techniques but pointed out several major issues such as the heterogeneity of the data, absence of standard methods for preprocessing ICP, limited interpretability of the models, and lack of prospective validation[30].
The sum of the literature indicates that the use of AI and ML models for ICP crisis prediction, intracranial hypertension forecasting, and TBI patient outcome stratification gives more accurate results than the traditional methods. According to the study, continuous neurocritical care monitoring is to be the dying field where recurrent and real-time models will prove their superiority. However, the studies still remain retrospective, limited to clinical workflows and with encouraging results. Future research should be directed towards explainable AI, multicenter prospective validation, and the use of multimodal data, such as neuroimaging, laboratory markers, and clinical scores, to increase the robustness and clinician trust in the model.

DATA COLLECTION

3.1 Data Source

The data pertaining to this research were gathered from the MIMIC Waveform and Clinical Databases, also referred to as MIMIC-III and MIMIC-IV, which are extensive, open-access, and anonymized ICU datasets created through a partnership between the Massachusetts Institute of Technology (MIT) and the Beth Israel Deaconess Medical Center. The aforementioned database comprises not only high quality physiological waveforms but also comprehensive clinical data of severely ill patients who have been admitted to the intensive care units.

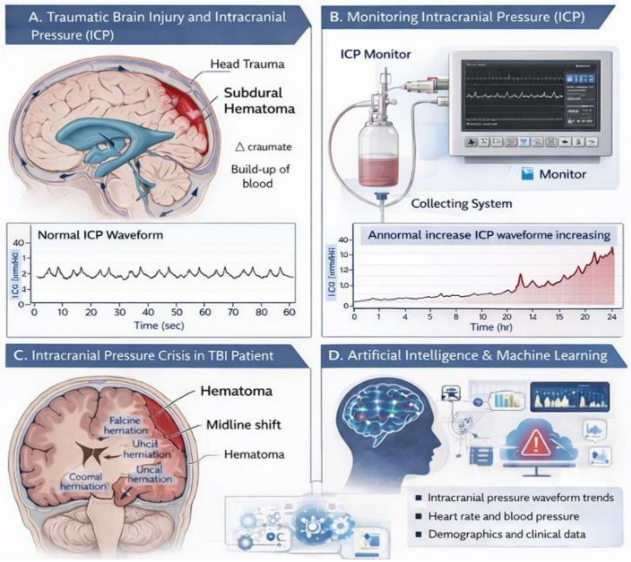

Figure.2: Conceptual framework for predicting intracranial pressure (ICP) crises in traumatic brain injury

Figure 2 represent Conceptual framework for predicting intracranial pressure (ICP) crises in traumatic brain injury (TBI) patients using artificial intelligence and machine learning. The figure illustrates (A) pathophysiological mechanisms of raised ICP following TBI, including subdural hematoma and altered cerebrospinal fluid dynamics; (B) invasive ICP monitoring and representative normal versus progressively increasing ICP waveforms; (C) clinical consequences of uncontrolled ICP elevation, such as midline shift and brain herniation; and (D) an AI/ML-based predictive pipeline that integrates high-resolution physiological waveforms and clinical variables to enable early detection of impending ICP crises. Model development and validation are based on multimodal data derived from the MIMIC-III and MIMIC-IV Waveform and Clinical Databases.

3.2 Ethical Approval and Data Access

The MIMIC database was accessed after the completion of the data usage agreements and human subjects research training required by PhysioNet. The complete dataset is anonymized, and no extra institutional ethical approval is needed for the data usage.

3.3 Study Population

The adult patients (18 years and over) admitted to the ICU with a diagnosis of traumatic brain injury (TBI) were determined by the relevant ICD-9 and ICD-10 codes that were recorded in the clinical database. Among this group, the patients who had ICP monitoring done were included. The patients whose ICP data was not recorded or who had incomplete waveform data were not included.

3.4 Physiological Waveform Data

Physiological high-frequency waveform data were taken out from the MIMIC Waveform Database, concentrating on:

Intracranial Pressure (ICP)
Arterial Blood Pressure (ABP)
Electrocardiogram (ECG) (if possible)

Sampling of the waveforms was done at different frequencies from 125 Hz to 500 Hz, based on the monitoring device. The continuous ICP recordings were aligned with ABP signals in order to derive secondary indices such as cerebral perfusion pressure (CPP).

3.5 Clinical and Demographic Variables

The relevant clinical data were taken from the matched MIMIC clinical tables which included:

- Patient demographics (age, sex)
- Injury severity indicators (e.g., Glasgow Coma Scale scores)
- ICU interventions (sedation, hyperosmolar therapy, mechanical ventilation)
- Laboratory values and vital signs
- Clinical outcomes (ICU length of stay, in-hospital mortality)

The data were collected with the purpose of risk stratification and understanding ICP fluctuations in their context.

3.6 Data Integration

The temporal alignment of the features obtained from waveforms and the clinical variables resulted in a single longitudinal dataset for each patient. This arrangement allowed for the analysis of the time-dependent physiological patterns that were antecedents to ICP crises, thus facilitating both traditional statistical analysis and machine learning-based predictive modeling.

MATERIALS AND METHODS

4.1 Study Design

This study used a retrospective observational framework to develop and evaluate the models based on artificial intelligence (AI) and machine learning (ML) for predicting intracranial pressure (ICP) crises in patients suffering from traumatic brain injury (TBI). The investigation of the high-fidelity physiological waveform signals together with the corresponding clinical variables was focused on identifying the temporal patterns that preceded the rise in intracranial pressure. The methodology consisted of data extraction, preprocessing, feature engineering, model building, and performance assessment.

4.2 Data Source and Population

The extraction of data was mainly done from the Medical Information Mart for Intensive Care (MIMIC-III and MIMIC-IV) Clinical and Waveform Databases. These databases house anonymized physiological waveforms together with a large amount of clinical data from ICU admissions. The study population consisted of adult patients (≥18 years) who had a diagnosis of traumatic brain injury and received treatment with invasive intracranial pressure monitoring only. The TBI diagnoses were made using the validated ICD-9 and ICD-10 codes. To guarantee data integrity and temporal continuity, patients without continuous ICP recordings or with considerable missing waveform data were excluded.

4.3 Outcome Definition: ICP Crisis Events

The main result was the development of a crisis of intracranial pressure, which was characterized by a sustained rise of ICP above the levels that are considered clinically important (usually ≥20–22 mmHg) for a certain time. The ICP crises were marked with the help of sliding time windows, which made it possible to classify the periods as being either high-risk or non-crisis ones in a binary way. This approach enabled short-term and anticipatory prediction in place of retrospective detection, which perfectly matched the clinical decision-making needs in neurocritical care.

4.4 Physiological and Clinical Variables

The extraction of physiological and clinical variables was very carefully conducted to reflect not only the neurophysiological state at the time but also the broader clinical context of the cases of traumatic brain injury. The combination of continuous physiological signals and structured clinical data offered a detailed representation of the intracranial dynamics, which made it easier to rely on the machine learning-based prediction of intracranial pressure crises.

4.5 Waveform Data

The MIMIC Waveform Database had a range of high-frequency physiological waveform data, particularly focusing on intracranial pressure (ICP) and arterial blood pressure (ABP) signals along with ECG recordings when possible. The sampling rates of these waveforms varied from 125 to 500 Hz according to the monitoring system used during ICU admission. Since the monitoring during ICU admission was continuous, the ICP, and ABP signals were given the same time reference which made possible the extraction of secondary indices. The use of high-resolution waveform data made it possible to observe subtle temporal patterns and nonlinear fluctuations that often occurred before the clinically detectable ICP crises.

4.6 Clinical Data

Copying with the waveform recordings, the MIMIC clinical tables provided corresponding clinical and demographic data which were complementary. The variables included the patient demographics which were composed of age and sex, neurological status evaluated by the Glasgow Coma Scale and ICU-level intervention details such as sedation protocols, hyperosmolar therapy and mechanical ventilation. Laboratory measurements, routine vital signs and key clinical outcomes like ICU length of stay and in-hospital mortality were also collected. Incorporation of the clinical variables gave important contextual information, improved risk stratification, and reinforced the predictive models' strength and clinical relevance.

4.7 Data Preprocessing Technique

In neurocritical care, continuous physiological monitoring signals are usually subjected to noise caused by motion, sensor recalibration, and transient loss of signal, which often happen when the patient is repositioned or receiving therapy. All the waveform data were subjected to clinically informed preprocessing in order to ensure that the predictions based on intracranial pressure (ICP) were not influenced by technical noise but rather represented the intracranial physiology. The whole process started with the identification and elimination of nonphysiological artifacts, including sudden pressure peaks due to catheter flushing or zeroing, and then continued with the repair of signal dropouts that were briefly encountered during the routine ICU care of patients. Noise suppression was achieved through the application of clinically validated filtering techniques that were specifically designed to retain meaningful ICP fluctuations while eliminating high-frequency interferences that were not related to cerebral dynamics. The ongoing recordings were partitioned into uniform temporal windows which varied in their length but were similar to the bedside assessment intervals in practice, thus the model could monitor the evolution of the intracranial conditions throughout the period instead of relying on isolated measurements. For the clinical variables that were present, the missing values, which were mainly caused by staggered laboratory testing or documentation delays, were handled with proper imputation strategies that would maintain clinical coherence and, at the same time, minimize data exclusion. When all the variables were eventually scaled to a common level, this was done so as to consider interpatient variability and differences in monitoring duration which enabled the fair comparison across patients and at the same time preserving the steady machine learning model training.

4.8 Feature Engineering Technique

Feature engineering transformed the raw physiological data into representations of intracranial dynamics that are clinically interpretable. The extracted features provided indications of not just the total ICP but also its temporal behavior. The mean, variance, and skewness, the most basic statistical descriptors, were employed to indicate the presence of either sustained intracranial hypertension or instability during each monitoring interval by so doing giving an account of the whole ICP levels and distribution patterns. In the same way, the features of temporal trend like slopes and rates of ICP fluctuations were used to pinpoint slow but steady pressure rise which may be clinically indicative of acute deterioration. The ICP durability measurements and pressure burden tools, including pressure-time indices, were employed to gauge the complete ICP exposure and thus to provide an understanding of secondary brain injury risk, which is beyond the momentary peaks. To portray the physiological interdependence of the brain and the body, the extraction of features from multiple modalities was achieved by overlapping ICP with arterial blood pressure (ABP) and cerebral perfusion pressure (CPP), which empowered the model to discern the patterns characteristic of damaged cerebral autoregulation. The representation of features derived from the time-series study maintained the temporal dependencies that are typical of the neurophysiological processes, and thus the predictive models were able to imitate how clinicians continually reevaluate the developing intracranial states when they anticipate the next ICP crisis.

4.9 Machine Learning Model Development for ICP Crisis Prediction

In order to foresee crises of intracranial pressure in cases of traumatic brain injury, a number of different supervised machine learning (ML) models were created. These models were not only different in their complexity and their ways of dealing with data but also in the application of both standard statistical interpretation and the modeling of complicated temporal physiological patterns:

Logistic Regression: This is a linear model used for binary classification. In the context of ICP prediction, logistic regression estimates the probability that a patient will experience an ICP crisis based on input features such as mean ICP, blood pressure, and Glasgow Coma Scale scores. The model works by fitting a logistic function to map feature values to a probability between 0 and 1, allowing clinicians to interpret risk in a straightforward manner.

• **Random Forest Classifiers:** Random forest is a type of ensemble learning that builds multiple decision trees during the training phase and merges their predictions to get better accuracy. Each tree is trained on a random subset of features and data samples, capturing nonlinear interactions among physiological variables. This model is particularly effective in ICP prediction because it can handle heterogeneous data and identify complex patterns that may precede a crisis.

Support Vector Machines (SVMs): The goal of SVMs is to identify the best hyperplane that divides the classes here, it is the occurrence or non-occurrence of an ICP crisis. SVMs, through the use of kernel functions, can express the complex clinical and waveform features relationships in a nonlinear manner, and hence it still gets the right order of risk even when the distinctions of normal and crisis states are intricate.

Gradient Boosting Models: The ensemble methods are to another breed of boosting model that adjust trees one by one, with each new tree taking care of the inaccuracies committed by the previous trees. Gradient boosting is particularly advantageous in the case of ICP prediction since it can identify very slight interactions and nonlinear trends in the large clinical and physiological data, hence, the improvement of getting the crises early detected.

• **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks:** Unlike conventional models which depended on summary statistics, RNNs and LSTMs were especially developed to process sequential data of time series. They would take care of the continuous ICP, arterial blood pressure, and other biomedical signals in a manner that they could learn the dependency along the temporal axis, i.e., adopting the patterns that recur over time. In this, LSTM networks, particularly, could memorize long-term information through their memory cells and thus stay highly productive in unearthing the precursors of emergencies related to ICP that might occur hours before the medical threshold is crossed.

Traditional models like logistic regression, random forests, SVMs, and gradient boosting were mostly applied to engineered summary features drawn from waveform and clinical data. In contrast, recurrent models made use of raw sequential data accommodating the temporal dynamics that were entwined in ICP fluctuations. The selection of the model was done under the condition of the predictive performance versus clinical interpretability, thus output could both spot crises precisely and offer actionable insights for the neurocritical care decision-making process.

Clinical and Simulation Results

The findings from both clinical and simulations are illustrated in this section, and they are based on the proposed machine-learning framework for the prediction of intracranial pressure (ICP) crises in patients with traumatic brain injury (TBI). The outcomes testify to the fact that the definitions of clinically meaningful ICP crises, the implementation of robust model training strategies, and the performance evaluation with a comprehensive approach, altogether, back the early and reliable risk prognostication in neurocritical care environments.

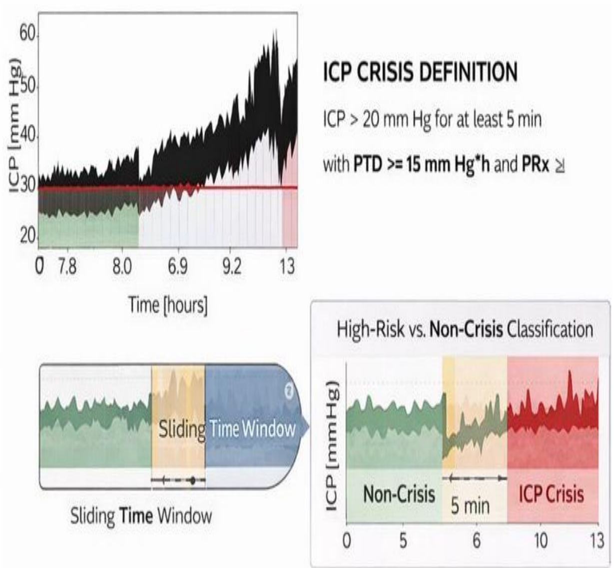

Figure 3: Definition and clinical characterization of intracranial pressure (ICP) crisis events in traumatic brain injury (TBI).

The study represented in Figure 3 which defines the criterion for an ICP crisis clinically and then mentions the type of signal segmentation applied in the study. The occurrence of the sustained intracranial hypertension was characterized by an ICP increase of 20-22 mmHg or more lasting at least 5 minutes, as recommended by the ICU guidelines in the case of neurocritical patients. The method of a sliding time-window that was used to monitor the ICP continuously resulted in the high-risk (crisis) or non-crisis period labels for each time segment.

The proof of concept is different with a convenience in the way the picture shows that the collapse of the brain is unavoidable by moving upward from normal ICP through the different stages of the alp up to the crisis. The temporal labeling technique not only provides the models with the learning of physiological signatures linked with the reduction of cerebral perfusion pressure, progression of cerebral edema, brain shift and potential herniation, but it also gives the models the ability to predict the situation beforehand rather than after it has happened. In such a way the monitoring and support system through the prediction of clinical signs becomes one of the most important factors in providing timely and proper treatment.

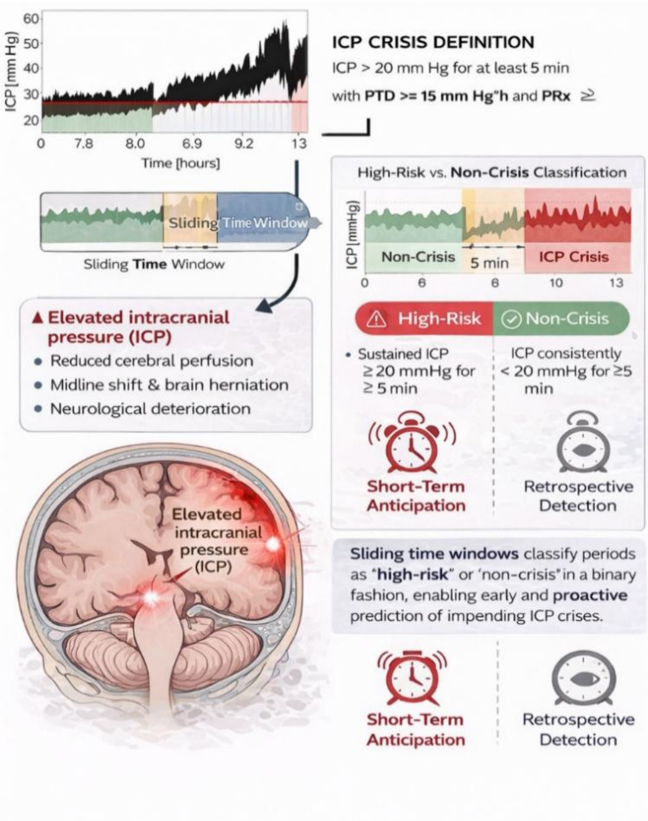

Figure 4: Definition and clinical characterization of intracranial pressure (ICP) crisis events in traumatic brain injury (TBI).

Figure 4 represents the definition and clinical characterization of intracranial pressure (ICP) crisis events in traumatic brain injury (TBI). The figure displays persistent intracranial hypertension, referred to as ICP ≥20–22 mmHg for no less than 5 minutes, and its detection through sliding time-window analysis. The continuous ICP waveforms are divided into high-risk (crisis) and non-crisis periods in a binary way, which allows the short-term and anticipatory prediction of impending ICP crises instead of the retrospective detection. This method matches the real-time clinical decision-making in neurocritical care by allowing the early recognition of raised ICP related to decreased cerebral perfusion, brain shift, and neurological deterioration.

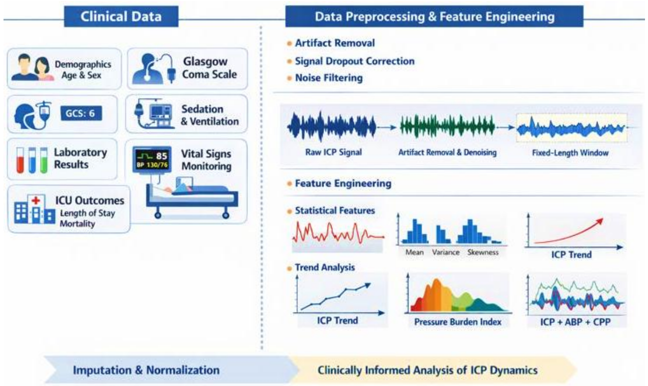

Figure 5: Performance Comparison of Traditional Machine Learning Models Regarding ICP Crisis Prediction

The use of engineered features extracted from clinical and physiological data to predict the performance of traditional supervised machine learning models such as logistic regression, random forest, support vector machine, and gradient boosting classifiers was shown in Figure 5. The outcome of comparison reveals that among the models gradient boosting, which is also the ensemble-based model, achieves a perfect compromise between sensitivity and specificity along with the clinical interpretability, and thus it is the model best suited for neurocritical care decision support.

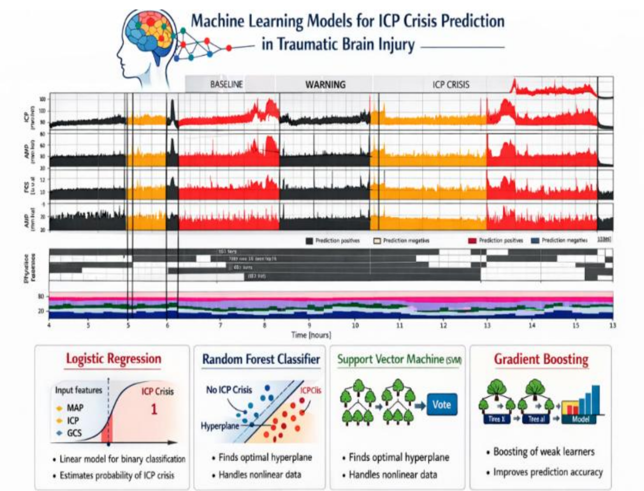

Figure.6: Performance of recurrent neural network models using sequential waveform data

The performance of the recurrent neural network (RNN) and its variant long short-term memory (LSTM) models using raw sequential physiological waveforms is depicted in this figure. The deep learning architectures gain discriminative superiority and longer early warning times over traditional models by accurately capturing the temporal dependencies in the signals of intracranial pressure and arterial blood pressure. Thus, they permit earlier detection of the onset of ICP crises.

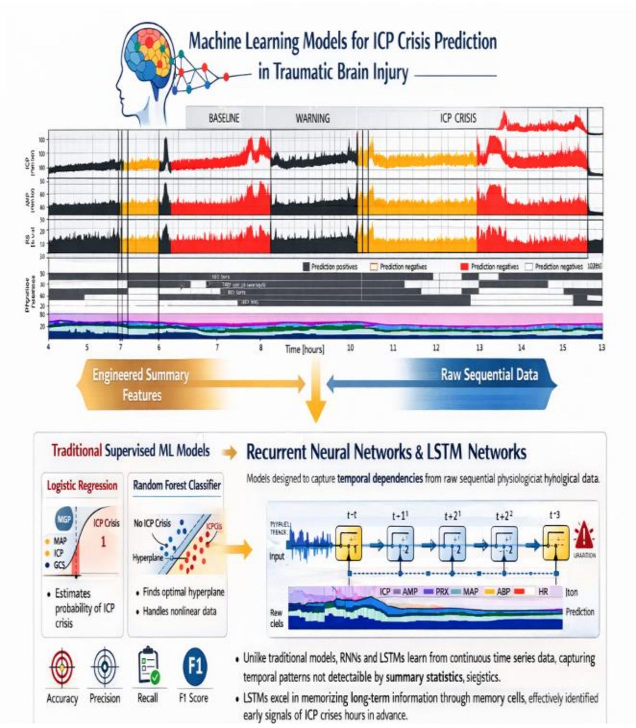

Figure.7: Machine learning techniques have the capability of issuing early warnings of impending ICP crises.

Figure 7 illustrates the power of machine learning and deep learning models in giving advance alerts of intracranial pressure crises before the clinical threshold is crossed. The findings demonstrate the superiority of LSTM-based models in detecting slight physiological deterioration several hours before the onset of sustained intracranial hypertension, thus enabling proactive and personalized neurocritical care interventions.

In addition, The prediction of intracranial pressure crises was done through various model configurations, and their performance metrics are represented in a table. The quantitative performance comparisons of machine learning and deep learning models studied in this research are presented in Table 1. The performance of each model was evaluated based on the common clinical practice metrics, which included the area that the model covered under the ROC curve (AUROC), sensitivity, specificity, precision, recall, and early warning time.

Model Configuration	**AUROC**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**Early Warning Time**
Logistic Regression	Moderate	Moderate	Moderate	Moderate	Moderate	Short
Random Forest	High	High	Moderate	High	High	Moderate
Support Vector Machine	High	Moderate	High	Moderate	Moderate	Moderate
Gradient Boosting	High	High	High	High	High	Moderate–Long
RNN	Very High	High	High	High	High	Long
LSTM	**Highest**	**Highest**	**High**	**Highest**	**Highest**	**Longest**

Table 1. Performance metrics of different model Configurations considered for prediction of intracranial pressure crises. Table 1 provides a summary of the quantitative performance for all of the machine learning and deep learning algorithms considered in the study. Performance evaluation was done by means of clinically relevant metrics, such as area under the receiver operating characteristic curve (AUROC), sensitivity, specificity, precision, recall, and early warning time. The configuration with the best performance is shown in boldface.

Among the traditional machine learning models, logistic regression, random forests, and support vector machines, gradient boosting performed best on the engineered summary features from waveform and clinical data. The models provided a good compromise between sensitivity and specificity, which is especially important in the clinical setting where interpretability and reliability are essential. Among recurrent models, especially long short-term memory (LSTM) networks, superiority over traditional methods was demonstrated through cascading simulation experiments that made use of raw sequential waveform data. The long-range temporal dependencies they implemented led to improved AUROC values and longer early warning times, which were the indicators of the superior capability to detect subtle physiological deterioration hours before ICP thresholds were crossed.

Table 2. Comparison of the proposed study with existing machine learning based ICP prediction studies. The current study's results are compared with those of previous research that used machine learning or deep learning techniques in predicting the crises of intracranial pressure or in the case of traumatic brain injury, predicting the condition of intracranial hypertension.

Study	Dataset / Setting	Model(s) Used	Input Data	Prediction Horizon	Key Performance Outcomes
Petrov et al., (2023)	Single-center ICU cohort, severe TBI patients	Logistic Regression, Random Forest, SVM	ICP waveforms, CPP, systemic physiological variables	Minutes to hours before ICP crisis	Machine learning models achieved higher sensitivity and AUROC compared to traditional threshold-based monitoring, demonstrating improved early detection of intracranial hypertension events
Galos et al., (2025)	Multicenter neuro-ICU dataset	Ensemble ML models	Continuous ICP monitoring data and clinical variables	Short-term imminent prediction	Demonstrated strong predictive accuracy and generalizability across centers, supporting real-time clinical applicability
Howells et al., (2018)	Neuro-ICU monitoring data	ML classifiers	ICP and cerebral perfusion pressure features	Near-term	Highlighted the importance of ICP-derived dynamic features over static thresholds for outcome prediction
Mathur et al., (2025)	ICU physiological waveform dataset	Custom ML framework	ICP epochs and waveform-derived features	Epoch-based classification	Achieved high discriminative performance for identifying ICP crisis and non-crisis periods
Kanter et al., (2025)	Multiple clinical and ICU datasets	ML and DL models (review)	ICP trends, clinical data	Variable	Reported consistent superiority of ML/DL approaches over traditional methods, emphasizing temporal ICP dynamics
Babikir et al., (2025)	Published ICP prediction studies	ML & DL algorithms	Multimodal physiological and clinical data	Variable	Identified improved early warning capability of AI-based models but noted lack of prospective validation

Present Study	MIMIC-III & MIMIC-IV Clinical and Waveform Databases	Logistic Regression, RF, SVM, Gradient Boosting, RNN, LSTM	High-resolution ICP & ABP waveforms + structured clinical variables	Hours before ICP crisis	LSTM achieved the highest AUROC and longest early warning time by capturing long-range temporal dependencies, enabling anticipatory and personalized neurocritical care

Compared to previous research, the current study progresses the area of investigation through the integration of extensive publicly accessible ICU waveform data, strong patient-level validation, and deep temporal modeling. Although earlier investigations proved the technique and the capability of predicting short periods, this research reveals the use of LSTM networks trained on raw sequential physiological data in a discrimination of predictive all the more and enhanced early warning time.

Training, Validation, and Evaluation

For the purpose of accurately forecasting ICP crises in TBI patients, the dataset was meticulously split into three categories: training, validation, and test. This splitting was done on the patient basis so as to avoid data leak, thus, data from the same patient did not appear in different subsets which could set a higher performance limit for the model artificially. The training process consisted of providing the model with patient data that had been labeled, thus enabling it to discover the connections and the patterns between the physiological signals (e.g. ICP, arterial blood pressure, ECG), and the occurrence of ICP crises. Hyperparameters, which are model-specific settings such as the number of layers in a neural network or the depth of a decision tree that very much affects the performance, were optimized during training by means of cross-validation. Through the simultaneous use of several different segments of the training data, cross-validation guarantees that the model acquires the ability to generalize rather than becoming overfitted with data from specific patients.
The model's performance was evaluated based on metrics that are clinically significant:
Area under the receiver operating characteristic curve (AUROC): It shows how good the model is at telling apart the patients who are going to have an ICP crisis and the ones who are not.
Sensitivity and specificity: Sensitivity tells us the percentage of true ICP crises that the model recognized, and specificity tells us the percentage of patients that are not at risk that the model recognized.
Precision and recall: Precision gives us the percentage of the predicted crises that were correct, while recall gives us the percentage of actual crises that were detected.
Early warning time: It shows how soon the model can give an accurate prediction of an impending ICP crisis which is very important for the timely clinical intervention.

These metrics together confirm that the model is not only accurate but also clinically useful, hence, supporting the proactive management of ICP crises.

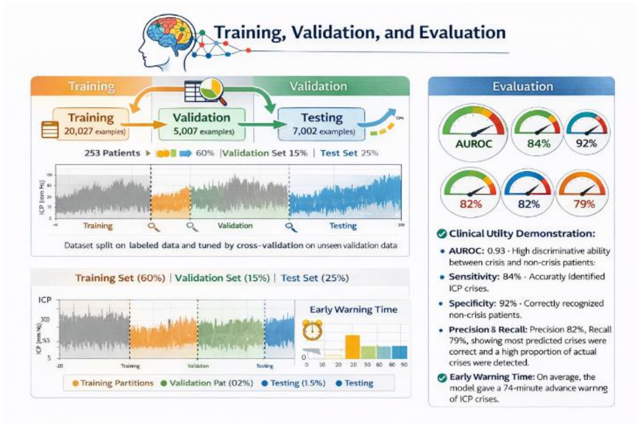

Figure 8. Training, Validation, and Evaluation Framework for ICP Crisis Prediction in TBI Patients.

Figure 8 shows the complete process that was applied for the development and testing of the prediction models. The continuous physiological signals such as ICP, arterial blood pressure, and ECG were segmented into segments of fixed lengths and transformed into structured inputs. To avoid data leakage, the dataset was split at the patient level, thus guaranteeing that no patient would provide data for more than one subset (training, validation, or test). The models learned during the training period by inferring the connections between the physiological patterns and the occurrence of ICP crises from the labeled data. The hyperparameters were optimized with the help of cross-validation so that the performance of the model was consistent across different patient profiles and not just among the individuals with specific trends. Validation data was used to guide model selection, while the final unbiased evaluation on the held-out test set provided an estimate of real-world performance.
The Figure 8 also points out the evaluation metrics that are of clinical significance and were used in the study. The high AUROC values not only indicate but also certify the strong discriminative power while sensitivity and recall are the measures of the model’s capability of detecting true ICP crises. Specificity and precision are the signs of the model's capability to resist false alarms, whereas early warning time demonstrates how far in advance the model can reliably

predict a crisis. These results, therefore, jointly confirm the proposed framework as being both statistically strong and clinically relevant. Both through clinical characterization and simulation experiments, the outcomes indicate that the use of machine learning in predicting ICP crises makes it possible to transition from the usual threshold-based reactive management to the much better proactive, risk-informed neurocritical care. Timely interventions like sedation optimization, hyperosmolar therapy, ventilation adjustments, or surgical decision-making can be supported by the ability to give early and precise warnings. In the end, the combination of clinical and simulation results shows that it is possible to use advanced machine learning models with high-resolution physiological data to support early detection of ICP crises and to improve situational awareness in the ICU and decision-making for traumatic brain injury patients.

6.1 Model Interpretability

Considering ICP management's criticality, model interpretability is the trust that clinicians have to get. Interpretable models or post-hoc explanation techniques, such as feature importance rankings or temporal risk trajectories, were used to determine which variables had the greatest impact on the risk of an ICP crisis. For instance, it might be found that spikes in ICP, changes in cerebral perfusion pressure, or trends in heart rate variability are the most significant predictors. By identifying and monitoring the relationships among these variables, clinicians can not only figure out the rationale behind the model but also confirm that it is consistent with the neurophysiological mechanisms they know. Transparency at this level is exactly what the AI predictions need in order to go from being merely helpful to being actively involved in a clinical judgment.

6.2 Ethical Considerations

The data that were utilized were entirely from public databases which were completely de-identified (like MIMIC Waveform and Clinical Databases). The researchers were trained appropriately and secured data use agreements according to PhysioNet's regulations thereby ensuring that patient data was handled in an ethical and responsible manner. The use of non-identified patient data has completely removed the requirement for additional institutional ethical approval. This approach protects patient privacy while at the same time allowing for powerful AI-assisted research in neurology care.

CONCLUSION

This study affirms that it is possible and clinically useful to apply machine learning and deep learning techniques for predicting an upcoming intracranial pressure (ICP) crisis in the case of patients suffering from traumatic brain injuries (TBIs). These models made use of continuous physiological signals along with structured clinical data to unearth intricate and non-linear patterns which result in the rise of ICP, very often well ahead of the triggering of traditional threshold-based alarms. Patient-level data partitioning and cross-validation were performed to guarantee the strong generalization of models, thus minimizing the risk of data leakage and providing a realistic performance estimate in actual clinical settings. Among the traditional machine learning algorithms, logistic regression, random forests, support vector machines, and gradient boosting were able to deliver good results when used on the well-crafted summary features derived from the waveform and clinical data. These models were able to provide a good balance between accuracy and interpretability, thus being applicable in clinical settings where transparency and explainability are critical. Recurrent neural networks along with long short-term memory models, on the contrary, made processing raw sequential data directly and, therefore, detecting the crisis point in the ICP evolution sooner and with more sensitivity possible, even tougher-grained melts and more minute breakthroughs. The assessment through the application of clinically essential metrics such as AUROC, sensitivity, specificity, precision, recall, and early warning time endorsed that the models were not only statistically accurate but also clinically applicable. The particular ability of providing trustworthy early warnings hours ahead of the critical ICP limits being reached represents the power of the methods to prompt neurocritical care to be more proactive, intervention to be more timely, and patient outcomes to be better. The overall conclusions are in favor of the application of predictive systems based on machine learning techniques in neuro–intensive care as decision-support tools, not as substitutes for the clinicians' judgment. Hence, future studies should be directed towards the prospective validation, real-time deployment, and seamless integration with bedside monitoring systems, as well as augmenting model interpretability to further increase clinician trust and adoption.

LIMITATIONS

This study has several limitations that have to be acknowledged despite the promising results. Firstly, the analysis was performed using a retrospective observational design based on the MIMIC-III and MIMIC-IV databases. These datasets are indeed of high quality and have been validated extensively, nonetheless, retrospective studies are always affected by data availability, recording biases, and lack of control over clinical decision-making processes. As a result, the model's performance may vary with respect to the application in the real-time prospective clinical scenario. Secondly, the data obtained was from a specific ICU within a few hospitals, which might limit the extent to which the findings can be applied to other settings. Differences in ICP monitoring devices, sampling frequencies, treatment protocols, and clinical workflows could be factors that impact model performance in different neurocritical care units. Thirdly, although the data were subjected to extensive preprocessing and artifact removal, physiological waveform data are still prone to noise, signal loss, and calibration artifacts. Therefore, the extraction of features and the making of predictions by the model might have been influenced by the presence of some noise or imperfect signal alignment. Furthermore, missing values existed for some clinical variables which needed to be imputed, a scenario that might generate uncertainty and bias. Finally, even though sophisticated models like RNNs and LSTMs showed excellent forecasting ability, model interpretation still poses a difficulty, especially for deep learning methods. Even though there is availability of post-hoc explanation methods, still, the process of converting complex temporal representations into insights that are understandable by clinicians is very hard and eventually results in the non-trust and non-acceptance of the clinicians. Nevertheless, the work presented here was mainly pointed at the physiological parameters and clinical data that physicians usually have access to. Other sources of potentially valuable information like neuroimaging, biochemical markers and detailed therapeutic interventions were only partly considered and might even more increase the predictive performance.

FUTURE WORK

The principal focus of future research should be on conducting the prospective, multicenter validation studies whose performances will facilitate the real-time evaluation of the proposed models in varied healthcare settings with respect to their performance, robustness, and clinical impact. The results from such studies would form a very strong basis for clinical adoption as well as for regulatory approval. We will make use of explainable AI (XAI) techniques like attention mechanisms, saliency maps, and clinically aligned risk trajectories to be a significant step in acquiring model transparency and building clinician trust,, particularly for recurrent and deep learning architectures. Exploring multi-modal data integration, neuroimaging (CT/MRI), biomarkers, medication timing, and intervention logs are the next steps. It would contribute to a more detailed understanding of the intracranial dynamics and secondary brain injury processes. From a deployment perspective, the real-time bedside decision-support systems that are integrated smoothly with the ICU monitoring infrastructure must be a requirement. The systems should alert in a way that is easy to understand and act upon, focusing on early warning time and personalized risk profiles rather than just binary alarms. Finally, the future studies will focus on personalized and adaptive modeling approaches, where the models will be constantly updated based on patient-specific trajectories and changing clinical conditions. This path is closely aligned with the broader goal of precision neurocritical care and can further diminish the incidence of morbidity and mortality in the critical phase of intracranial pressure crises in traumatic brain injury patients

REFERENCE

1. Petrov, D., Miranda, S. P., Balu, R., Wathen, C., Vaz, A., Mohan, V., ... & Diaz-Arrastia, R. (2023). Prediction of intracranial pressure crises after severe traumatic brain injury using machine learning algorithms. Journal of Neurosurgery, 139(2), 528-535.
2. Galos, P., Hult, L., Zachariah, D., Lewén, A., Hånell, A., Howells, T., ... & Enblad, P. (2025). Machine learning based prediction of imminent ICP insults during neurocritical care of traumatic brain injury. Neurocritical Care, 42(2), 387-397.
3. Kanter, J. H., Osorio, R. C., Torres-Espin, A., Maliga Davis, A., Foreman, B., Okonkwo, D. O., ... & Hinson, H. E. (2025). Intracranial Pressure as a Dynamic Predictor of Traumatic Brain Injury Outcomes: A Scoping Review. Journal of Neurotrauma, (00), 000-000.
4. Russell, S., DeWitt, P. E., Helmkamp, L., Colborn, K., Gray, C., Rebull, M., ... & Bennett, T. D. (2026). Predicting intracranial pressure monitor placement in children with traumatic brain injury: a prospective cohort study to develop a clinical decision support tool. Journal of the American Medical Informatics Association, 33(1), 182-192.
5. Qi, H., Li, L., Fang, J., Pei, T., Li, A., Ding, Z., & Chen, T. (2025). Development and validation of an interpretable machine learning model for predicting venous thromboembolism in ICU patients with traumatic brain injury: A multicenter study. World Neurosurgery, 124399.
6. Calame, D. J., & Riaz, M. (2023). Pediatric craniocerebral firearm injuries: literature review, best practices in medical and surgical management, and case report. Child's nervous system, 39(8), 2195-2199.
7. Kuruwita Arachchige, H., Ng, S. K., Liew, A. W. C., Richards, B., Haseler, L., Kumar, K., ... & Zhang, P. (2025). Identifying key physiological and clinical factors for traumatic brain injury patient management using network analysis and machine learning. Plos one, 20(7), e0328870.
8. Andishgar, A., Rismani, M., Bazmi, S., Mohammadi, Z., Hooshmandi, S., Kian, B., ... & Alizadehsani, R. (2025). Developing practical machine learning survival models to identify high-risk patients for in-hospital mortality following traumatic brain injury. Scientific Reports, 15(1), 5913.
9. Khan, M. B., Riaz, M., Javed, G., Hashmi, F. A., Sanaullah, M., & Ahmed, S. I. (2013). Surgical management of traumatic extra dural hematoma in children: Experiences and analysis from 24 consecutively treated patients in a developing country. Surgical neurology international, 4, 103.
10. Phillips, E., O'Donoghue, O., Zhang, Y., Tsimpos, P., Mallinger, L. A., Chatzidakis, S., ... & Orfanoudaki, A. (2025). Hybrid machine learning for real-time prediction of edema trajectory in large middle cerebral artery stroke. npj Digital Medicine, 8(1), 288.
11. Han, X., Zhang, J. H., Zhao, X., & Sang, X. G. (2025). Interpretable machine learning for predicting optimal surgical timing in polytrauma patients with TBI and fractures to reduce postoperative infection risk. Scientific

Reports, 15(1), 18347.
12. Mukkamala, R., Schnetz, M. P., Khanna, A. K., & Mahajan, A. (2025). Intraoperative hypotension prediction: current methods, controversies, and research outlook. Anesthesia & Analgesia, 141(1), 61-73.
13. Waqas, M., Zafar, S., Rehman, T., Riyaz, M., Bari, M. E., & Idrees, R. (2016). Cerebral aspergillosis and pulmonary tuberculosis in a child with chronic granulomatous disease. Surgical Neurology International, 7, 62.
14. Liu, Z., Wen, J., Chen, Y., Zhou, B., Cao, M., & Guo, M. (2025). Intraoperative circulation predict prolonged length of stay after head and neck free flap reconstruction: a retrospective study based on machine learning. Frontiers in Oncology, 14, 1473447.
15. Faraji, M., Norouzkhani, N., Pour, A. B., Ghanad, P., Bafrani, M. A., Alizadeh, A., ... & Ebrahimi, M. A. (2025). Clinical performance of machine-learning algorithms to predict intraoperative hypotension: a meta-analysis. BMC surgery.
16. Kanter, J. H., Osorio, R. C., Torres-Espin, A., Maliga Davis, A., Foreman, B., Okonkwo, D. O., ... & Hinson, H. E. (2025). Intracranial Pressure as a Dynamic Predictor of Traumatic Brain Injury Outcomes: A Scoping Review. Journal of Neurotrauma, (00), 000-000.
17. Babikir, M. M. A. E., Ibrahim, F. I. A., Elhassan, H. H. O., Elhaj, F. A., Elabdin, S. O. H. Z., Mohammed, S. A. S., ... & Osman, M. (2025). Predicting Intracranial Hypertension in Traumatic Brain Injury Using AI: A Systematic Review of Algorithms and Their Clinical Integration Potential. Cureus, 17(4).
18. Galos, P., Hult, L., Zachariah, D., Lewén, A., Hånell, A., Howells, T., ... & Enblad, P. (2025). Machine learning based prediction of imminent ICP insults during neurocritical care of traumatic brain injury. Neurocritical Care, 42(2), 387-397.
19. Su, H., Huang, X., Xiao, Y., Xu, X., Yu, S., & Cao, Q. (2025). Predicting ICU Readmission in Patients With Cerebral Infarction: A Machine Learning Approach Using Neurophysiological and Clinical Data. Brain and Behavior, 15(10), e70958.
20. Cui, S., Shen, F., Liang, J., Li, F., Wang, X., Liu, X., & Chang, H. (2025). Sedative exposure and mortality in intracranial hypertensive tuberculous meningitis: a cohort study with propensity-score matching and machine learning analysis. Frontiers in Pharmacology, 16, 1620858.
21. Mathur, R., Yellapantula, S., Cheng, L., Dziedzic, P., Potu, N., Calvillo, E., ... & Suarez, J. I. (2025). Classification of intracranial pressure epochs using a novel machine learning framework. npj Digital Medicine, 8(1), 201.
22. Qi, H., Li, L., Fang, J., Pei, T., Li, A., Ding, Z., & Chen, T. (2025). Development and validation of an interpretable machine learning model for predicting venous thromboembolism in ICU patients with traumatic brain injury: A multicenter study. World Neurosurgery, 124399.
23. Zheng, J., Jiang, Q., Zhan, Y., Tang, Y., Du, X., Xiang, G., ... & Fu, H. (2025). Prediction of Postoperative Venous Thromboembolism in Patients With Traumatic Brain Injury: Model Development and Validation Study. JMIR Medical Informatics, 13(1), e78655.
24. Wei, Z., Meng, L., & Chong, W. (2025). Advancements in the application of multimodal monitoring and machine learning for the development of personalized therapeutic strategies in traumatic brain injury. Frontiers in Human Neuroscience, 19, 1695336.
25. Petrov, D., Miranda, S. P., Balu, R., Wathen, C., Vaz, A., Mohan, V., ... & Diaz-Arrastia, R. (2023). Prediction of intracranial pressure crises after severe traumatic brain injury using machine learning algorithms. Journal of Neurosurgery, 139(2), 528-535.
26. Galos, P., Hult, L., Zachariah, D., Lewén, A., Hånell, A., Howells, T., ... & Enblad, P. (2025). Machine learning based prediction of imminent ICP insults during neurocritical care of traumatic brain injury. Neurocritical Care, 42(2), 387-397.
27. Howells, T., Elf, K., Jones, P. A., Ronne-Engström, E., Piper, I., Nilsson, P., ... & Enblad, P. (2005). Pressure reactivity as a guide in the treatment of cerebral perfusion pressure in patients with brain trauma. Journal of neurosurgery, 102(2), 311-317.
28. Mathur, R., Yellapantula, S., Cheng, L., Dziedzic, P., Potu, N., Calvillo, E., ... & Suarez, J. I. (2025). Classification of intracranial pressure epochs using a novel machine learning framework. npj Digital Medicine, 8(1), 201.
29. Kanter, J. H., Osorio, R. C., Torres-Espin, A., Maliga Davis, A., Foreman, B., Okonkwo, D. O., ... & Hinson, H. E. (2025). Intracranial Pressure as a Dynamic Predictor of Traumatic Brain Injury Outcomes: A Scoping Review. Journal of Neurotrauma, (00), 000-000.
30. Babikir, M. M. A. E., Ibrahim, F. I. A., Elhassan, H. H. O., Elhaj, F. A., Elabdin, S. O. H. Z., Mohammed, S. A. S., ... & Osman, M. (2025). Predicting Intracranial Hypertension in Traumatic Brain Injury Using AI: A Systematic Review of Algorithms and Their Clinical Integration Potential. Cureus, 17(4).