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Intracranial Pressure Monitoring for Traumatic Injury Patients Using Hybrid Deep Learning Model

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Detecting and monitoring abnormalities in intracranial pressure (ICP) is crucial within intensive care units (ICUs) to avert life-threatening outcomes. Despite the widespread use of deep learning (DL) in clinical diagnosis, there has been limited research focused on applying DL techniques for continuous ICP monitoring. This work presents an efficient method that incorporates a hybrid model comprising a one- dimensional customized convolutional neural network and Long Short-Term Memory . The aim is to predict and continually assess ICP status, including normotension, and hypertension with subtypes such as secondary intracranial hypertension and idiopathic intracranial hypertension for the condition of brain injuries.The model's performance was evaluated to gauge its proficiency in predicting elevated intracranial pressure, revealing a high level of accuracy in classifying ICP levels within our dataset.

Keywords: Intracranial pressure, intensive care, idiopathic intracranial hypertension.

1. Introduction

TBI remains a significant global health concern, causing substantial mortality and disability rates worldwide. Patients afflicted with TBI necessitate immediate and intensive medical intervention within an Intensive Care Unit (ICU), where a multidisciplinary team of medical specialists provides essential care. In many instances of TBI, hemorrhage occurs, leading to elevated Intracranial Pressure (ICP).

Elevated ICP not only exerts dangerous pressure on vital brainstem structures but can swiftly escalate into life-threatening situations, underlining the critical importance of continuous and accurate intracranial pressure monitoring in TBI cases. Effective management and real-time monitoring of ICP are paramount, as they can significantly influence patient outcomes and mitigate the risks associated with high intracranial pressure. Recent advancements in medical science, particularly in the realms of intensive care and technology, have led to the development of sophisticated monitoring techniques and predictive models to enhance the precision and effectiveness of ICP management. This burgeoning field has witnessed a diverse range of studies, each contributing unique perspectives and methodologies.

From intensive care protocols that incorporate multimodal monitoring to innovative machine learning algorithms and noninvasive estimation techniques, the landscape of TBI management is continuously evolving. These advancements not only signify the progress in medical research but also underline the pressing need for accurate and real-time ICP monitoring. This study delves into the contemporary landscape of ICP monitoring and TBI management, surveying recent literature to understand the state-of-the- art techniques and methodologies. Understanding the nuances of these methodologies is crucial in refining existing protocols and exploring novel avenues for more effective and personalized TBI management. As the integration of technology and medical expertise continues to shape the future of healthcare, this study contributes to the ongoing discourse, paving the way for more precise, data-driven, and patient-centric approaches in the realm of TBI management and intracranial pressure monitoring.

2. Literature Survey

Guochang Ye, Vignesh Balasubramanian, John K-j Li , Mehmet Kaya et al.[1], predicts and categorizes intracranial pressure (ICP) events for patients with injuries in the brain using a recurrent neural network (RNN). RNN may have overfitting issues and struggle to generalize to new patients.

Hosseinali Khalili, Maziyar Rismani, Mohammad Ali Nematollahi et al.[2], tests several cutting-edge machine learning algorithms, such as Deep Learning, K nearest neighbor, Random Forest, Rule induction, and Naive Bayes. More assessment of the models under investigation is required. Make plans to prepare more adaptable datasets from various hospitals. More extensive datasets result in more reliable model evaluation and training. Ahammed Mekkodathil , Ayman

EI-Menyar , Mashhood Naduvilekandy , Sandro Rizoli and Hassan AI- Thani et al.[3], carries out a retrospective study for patients with penetrating injuries at the Hamad Trauma Center. The ATLS protocol, or Advanced Trauma Life Support, is utilized to evaluate trauma patients systematically. In order to create a reliable machine learning model for TBI prediction, future research will gather more diverse, representative, and unbiased datasets.

Jean-Denis Moyer , Patrick Lee , Charles Bernard et al.[4], uses a cross-sectional, retrospective, multicenter diagnostic design to estimate the need for neurosurgery within a day. For moderate and severe head injuries, emergency neurosurgery is predicted using machine learning (ML)-based models. Since the study was carried out in France, it might not be applicable to other nations with various healthcare systems. Robert McNamara , Shiv Meka , James Anstey , Daniel Fatovich , Toby Jeffcote , Andrew Udy et al.[5], Uses

ICP forecasting algorithm, tIH Prediction Algorithms. Nils Schweingruber , Marius Marc-Daniel Madar , Anton Wiehe , FrankRoder et al.[6], uses a single-center cohort to train the model, and it needs outside validation. Depending on the patient population and the kind of ICP probe being used, the model's performance may change. Preprocessing procedures and the caliber of the data gathered may also have an impact on the model's performance. Shiker S.Nair , Alina Guo , Joseph Boen , Ataes Aggarwal , Ojas Chahal ,Arushi Tandon et al.[7], included individuals with ECG, PPG, ABP, and ICP recordings for a minimum of five minutes who were at least eighteen years old. Selective pre-processing techniques used to identify high-quality waveform data may introduce bias and subjectivity into the training set, thereby jeopardizing the robustness and performance of the model.

Avika Trakulpanitkit , Thara Tunthanathip et al.[8], Uses regression model of Machine learning algorithm . ONSD measurement is significantly correlated with ICP measurement. Honghao Dai MS , Laura Pahren MS , Laura B Ngwenya MD PhD et al.[9], Add all patients who, over a two-year period, require intracranial neuromonitoring at a Level I trauma center due to severe traumatic brain injury. At the individual level, more accurate outcome prediction can be obtained through computational techniques that leverage the properties of the ICP signal.

Yeongho Choi , Jeong Ho Park , Ki Jeong Hong , Young Sun Ro , Kyoung Jun Song , Sang Do Shin et al.[10], gathers information from three teaching hospitals located in South Korea's cities. Therefore, in order to generalize the developed prediction model, external validation for other domains needs to be carried out.

3. Methodology Existing System

Currently, machine learning methods are commonly used for intracranial pressure (ICP) classification tasks, but they tend to exhibit lower accuracy compared to deep learning approaches.This difference in accuracy can be attributed to the inherent complexity of ICP data. Machine learning methods often rely on manually engineered features and algorithms, which may struggle to capture intricate patterns and nuances in ICP data.

Proposed System

ICP signals are collected from the CHARIS database, sourced from PhysioNet. This database serves as the primary data source for the analysis.

1. Before proceeding with the analysis, it's crucial to preprocess the ICP signals. In this step, the signals undergo filtering through a notch filter. This preprocessing helps prepare the data for effective model training.

2. Once the preprocessing stage is complete, the system progresses to the training phase. In this phase, the ICP signals are employed to train the hybrid model, which is designed to learn and capture underlying patterns and features within the ICP data.

3. After successful hybrid model training, the system is ready for the classification of ICP status. When new ICP data is input, it undergoes the same preprocessing steps as during training. The preprocessed ICP data is then fed into the customized hybrid model classifier. Leveraging its learned knowledge, the model continuously classifies ICP status,

categorizing it as either intracranial normotension (within normal pressure ranges) or intracranial hypertension (elevated pressure) with subtypes like secondary intracranial hypertension and idiopathic intracranial hypertension.

4. To evaluate the effectiveness of the hybrid model, the system analyzes the results in terms of various performance metrics.

ARCHITECTURE DIAGRAM

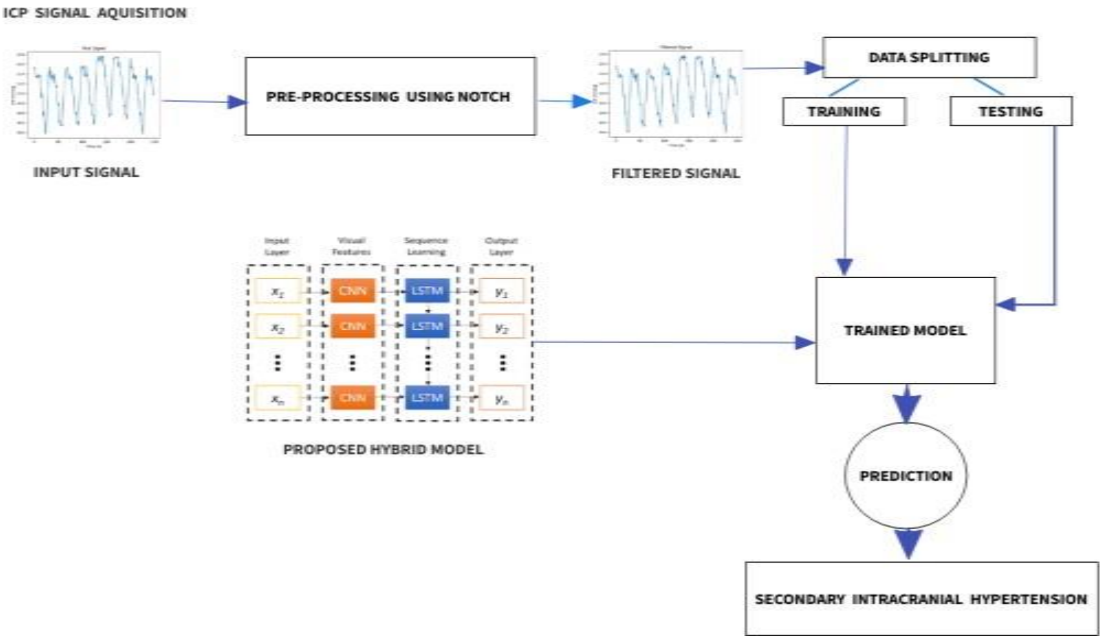

Fig 1: Architectural Diagram

ICP Signal Acquisition

The ICP signal acquisition module serves as the foundation for the entire system. By retrieving raw intracranial pressure data from the CHARIS database, this module establishes the basis for subsequent analysis and model development. The reliability of the acquired information directly influence the effectiveness of the pre-processing, model building, training, and classification stages.

Hence, this initial step is indeed vital, laying the groundwork for precise and meaningful results in the continuous monitoring and classification of intracranial pressure status.

Pre-processing

In this module, the acquired ICP signals undergo preprocessing. A Notch filter is applied to eliminate specific frequencies, ensuring a cleaner signal. Preprocessing enhances the quality of the data, making it suitable for accurate analysis.

Hybrid Model Building

The essence of the system lies in this module, where the hybrid model, integrating both a one-dimensional customized CNN and LSTM model, is constructed. The hybrid model architecture comprises both CNN and LSTM layers. The CNN layers are designed to extract spatial features from the ICP data, while the LSTM layers capture temporal dependencies, allowing the model to understand sequential patterns in the data.In the hybrid model building phase, the outputs from the final layers of both the 1DC-CNN and LSTM branches are concatenated. Subsequently, a dense output layer with a random forest activation function is introduced to generate multiclass predictions.

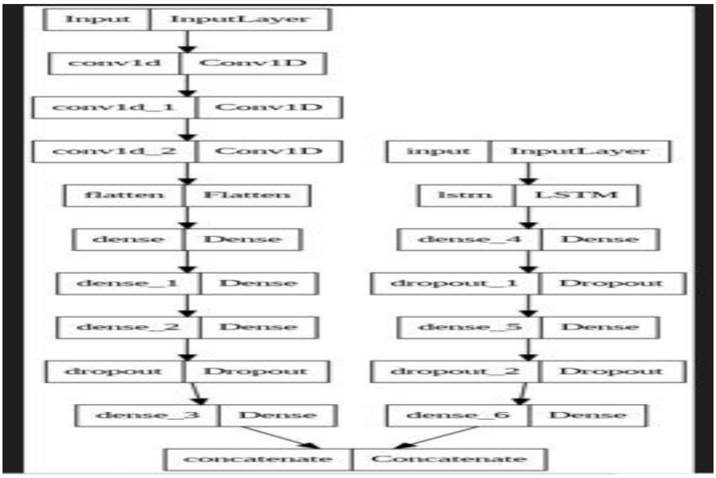

FIG 2: Integration of 1DC-CNN & LSTM

Train the Hybrid Model

In this module, the constructed hybrid model is trained using pre-processed ICP data. The model learns from the data, adjusting its parameters iteratively to minimize prediction errors. Training involves epochs of forward and backward passes, fine-tuning the model's weights for accurate classification.

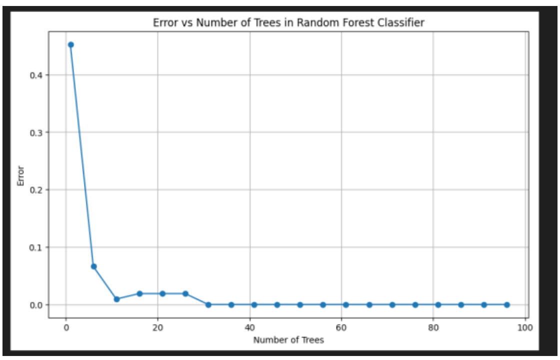

Fig 3: Error Vs No.Of Trees In RFC

MODEL TESTING

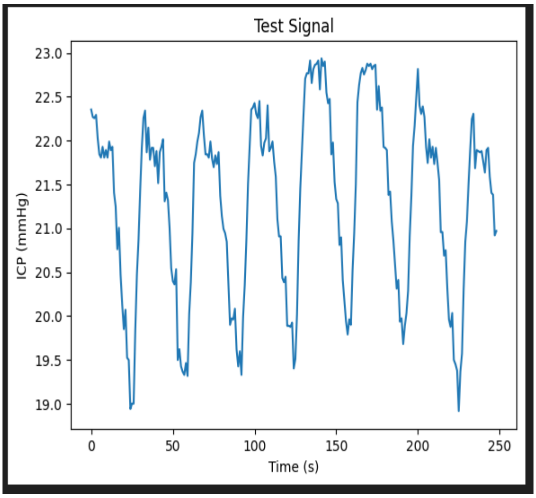

Fig 4: Test Signal

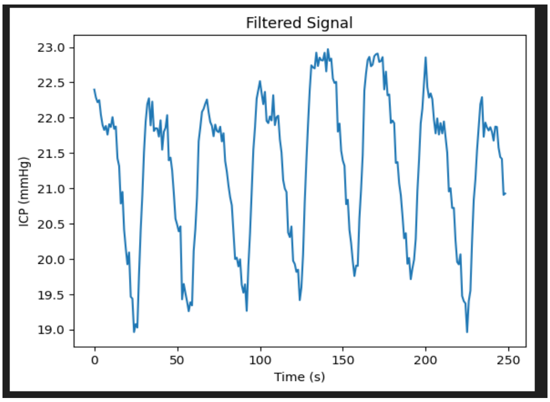

Fig 5: Filtered Signal

Classification

Once the hybrid model is trained, the classification module receives the test intracranial pressure (ICP) signal as input. The signal undergoes preprocessing and is then passed through the trained hybrid model. Leveraging the learned patterns and features, the model classifies the input data into either intracranial normotension or intracranial hypertension, including subtypes such as secondary intracranial hypertension and idiopathic intracranial hypertension, thus offering continuous and accurate classification of ICP status in real-time scenarios.

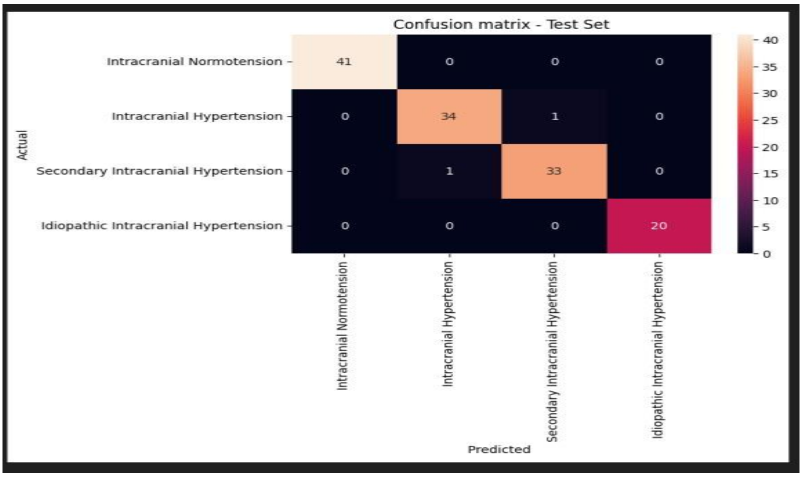

Fig 6: Classification Of Intracranial Pressure

4. Algorithm Description

Hybrid Model

The proposed work introduces a novel approach called the Hybrid Model. The approach integrates a one- dimensional customized convolutional neural network (1DC-CNN) and Long Short-Term Memory (LSTM) recurrent neural network for classification of Intracranial Pressure (ICP) status.The algorithm 1DC-CNN exhibits a multi-layered architecture, combining three convolutional and four dense layers, designed to achieve optimal performance.Simultaneously, the LSTM component captures temporal dependencies in sequential data through LSTM layers with ReLU activation functions and 100 units, followed by additional dense layers with 256, 128 and 64 neurons and also apply Dropout regularization with rates of 0.3 & 0.2. The training involves learning patterns from both structured and sequential aspects of the dataset.

Proposed Algorithm Structure (Hybrid Model)

Layer (type)	Output Shape	Param #	Connected to
Input (InputLayer)	[(None, 249, 1)]	0	[]
conv1d (Conv1D)	(None, 249, 64)	256	['Input[0][0]']
conv1d_1 (Conv1D)	(None, 249, 64)	12352	['conv1d[0][0]']
conv1d_2 (Conv1D)	(None, 249, 128)	24704	['conv1d_1[0][0]']
input (InputLayer)	[(None, 249, 1)]	0	[]
flatten (Flatten)	(None, 31872)	0	['conv1d_2[0][0]']
lstm (LSTM)	(None, 100)	40800	['input[0][0]']
dense (Dense)	(None, 512)	1631897 6	['flatten[0][0]']
dense_1 (Dense)	(None, 256)	131328	['dense[0][0]']
dropout_1 (Dropout)	(None, 256)	0	['dense_4[0][0]']
dense_2 (Dense)	(None, 128)	32896	['dense_1[0][0]']
dense_5 (Dense)	(None, 128)	32896	['dropout_1[0][0]']
dropout (Dropout)	(None, 128)	0	['dense_2[0][0]']
dropout_2 (Dropout)	(None, 128)	0	['dense_5[0][0]']
dense_3 (Dense)	(None, 64)	8256	['dropout[0][0]']
dense_6 (Dense)	(None, 64)	8256	['dropout_2[0][0]']
concatenate (Concatenate)	(None, 128)	0	['dense_3[0][0]', 'dense_6[0][0]']

Total params: 16636576 (63.46 MB)
Trainable params: 16636576 (63.46 MB)
Non-trainable params: 0 (0.00 Byte)

Fig 7: Hybrid Model's Structure

1D Customized CNN Model Structure (1DC-CNN)

Convolutional Layer

The first two layers employ a kernel size of 3x3 with 64 kernels, while the third convolutional layer uses a kernel size of 3x3 with 128 kernels.After the convolutional layers, a flatten operation is applied to prepare the data for the subsequent dense layers.

Dense Layers

Four dense layers follow the convolutional layers, housing 512, 256, 128, and 64 neurons, respectively.The last before dense layer incorporates a dropout mechanism with a rate of 0.1. This technique aids in mitigating overfitting and enhancing the model's generalization capabilities. In summary, the proposed algorithm boasts a sophisticated architecture comprising 1D convolutional layers, followed by densely connected layers.The incorporation of dropout mechanisms adds a layer of regularization, enhancing model robustness.

LSTM

The dimension of the data always determines how many nodes are in the input layer of a neural network (NN) with a single hidden layer. The input layer's nodes are connected to the hidden layer by links called "synapses." The relationship between every pair of nodes in the input to the hidden layer contains the weight coefficient, which acts as the signal decision-maker. After learning has ended, the Artificial Neural Network will have the right weights for every synapse.

5. Performance Measure

	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	41
1.0	0.97	0.86	0.91	35
2.0	0.87	0.97	0.92	34
3.0	1.00	1.00	1.00	20
accuracy			0.95	130
macro avg	0.96	0.96	0.96	130
weighted avg	0.96	0.95	0.95	130

Fig 8: Metric Results

ROC Analysis Result

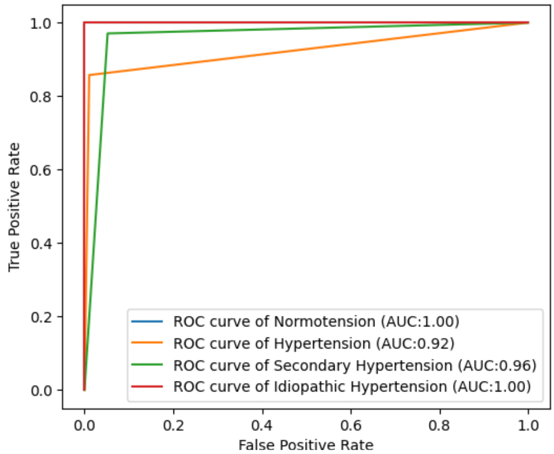

Fig 9: Roc Curve

The Receiver Operating Characteristic (ROC) curve analysis conducted for the classification of intracranial pressure (ICP) status yielded a commendable Area Under the Curve (AUC) value of 0.9706. This metric serves as a robust indicator of the model's ability to effectively differentiate between positive and negative instances for each ICP category. The AUC, ranging from 0 to 1, signifies the discriminative power of the model, where a higher value implies superior performance. In this context, an AUC of 0.9706 attests to the model's capability to discern between all classes based on predicted probabilities. Notably, this value surpasses random guessing (AUC of 0.5) and signifies robust predictive performance, indicating that the model's predictions exhibit substantial accuracy and reliability in distinguishing between different intracranial pressure statuses.

6. Conclusion

Intracranial pressure (ICP) monitoring stands as a pivotal element in the intensive care of patients, especially those with traumatic brain injuries. This work has introduced and implemented an advanced system for continuous ICP classification, leveraging a sophisticated hybrid model that integrates a one-dimensional customized convolutional neural network (1DC-CNN) and Long Short-Term Memory (LSTM) model. Through meticulous steps of collecting raw ICP signals, preprocessing, hybrid model training, and classification, the system has showcased its ability to accurately distinguish between intracranial normotension and intracranial hypertension, including subtypes such as secondary intracranial hypertension and idiopathic intracranial hypertension. By drawing data from the CHARIS database on PhysioNet and employing intricate preprocessing methods, such as the notch filter, the system ensured that the input ICP signals were optimally prepared for analysis.

The hybrid model, combining the spatial pattern recognition capabilities of the customized CNN and the temporal sequence learning of the LSTM, demonstrated its effectiveness in discerning intricate patterns within the ICP data. This hybrid model allows for a continuous and precise classification of ICP status, offering a more nuanced understanding of intracranial pressure dynamics. It provides efficacy in real-time clinical applications. A major development in continuous ICP tracking has been made with the inclusion of deep learning techniques in the form of a hybrid model, which provides a more accurate and comprehensive method of comprehending and treating intracranial pressure issues. The knowledge gained from this study advances the ongoing effort to improve patient treatment and outcomes in the field of managing traumatic brain injuries as medical science continues to advance.

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