Predicting ICP in patients with TBI: evaluation of a foundation model for time series

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Introduction: Patients with traumatic brain injury (TBI) often experience pathological increases in intracranial pressure (ICP), leading to intracranial hypertension (tIH) —a common and serious complication [1]. Early warning of an impending rise in ICP could potentially improve patient outcomes by enabling preemptive clinical intervention [2, 3]. However, the limited availability of patient data poses a challenge in developing reliable prediction models [4–6]. In this study, we aim to determine whether foundation models, which leverage transfer learning [7], may offer a promising solution.

Data: The training and internal validation data were from the high-resolution multimodal dataset from TRACK-TBI. After removing unrealistic signals, we ended up with 32 patients and a total of 83 recordings, comprising 5,142 hours of data. The data was pre-processed with the algorithm from [4] to end up with one ICP value for every minute. ICP is measured in mm Hg; normal values for a person in a supine position range between 0.9 and 16.3 mm Hg [8]. The Brain Trauma Foundation guidelines set the threshold for a tIH event at 22 mm Hg, though this is contested [1, 9].

Models: In this study, we compare three models: simple exponetial smoothing (ES) [10], a Recurrent Neural Network (LSTM) [11, 12], and the MOMENT model [13]. The main characteristics of the models can be seen in Table 1. For all models, the only input variable was ICP where the past 60-minutes were used as input to forecast the next 30-minutes.

Table 1. The characteristics of the models used.

Model	**Transfer learning**	**Extensive training**	**Input-length**	**Output-length**	**Univariate**
MOMENT	Yes	Yes (Fine-tuning)	512	Variable	Partly [a]
LSTM	No	Yes	Variable	Variable	No
ES	No	No	Variable	Variable	Yes

[a] It can independently model univariate time series.

Results: We see that the MOMENT model performs, based on the MSE and MAE, a little better than the LSTM, and both perform much better than the ES model (Table 2). The lowest MAE was 1.78 (MOMENT). The SD of the metrics is high for all models, which indicates heterogeneity in the data. The MOMENT model did converge in fewer epochs compared to the LSTM.

Table 2. Average internal validation performance over 5 CV folds, SD is in brackets.

Metric	MOMENT	LSTM	ES
MSE	9.06 (3.70)	10.19 (3.50)	22.56 (8.31)
MAE	1.78 (0.40)	1.86 (0.32)	3.04 (0.61)
90th percentile MAE	3.85 (0.78)	3.91 (0.72)	6.43 (1.31)
99th percentile MAE	9.45 (1.98)	11.13 (3.53)	14.48 (1.57)

In Figures 1 and 2 we zoom in on the predictions of the MOMENT and LSTM models. The black line indicates the observed signal and the colored lines indicate separate 30 minute predictions (every 10 minutes). It is evident that both models lack the ability to predict high-magnitude, low-frequency changes in the observed signal.

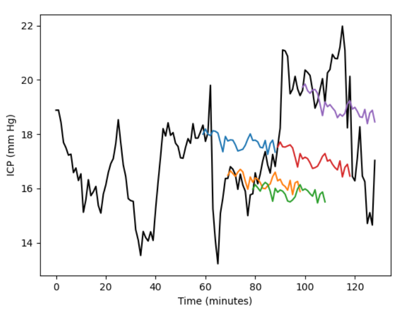

Fig. 1. 30-minute forecasts (MOMENT).

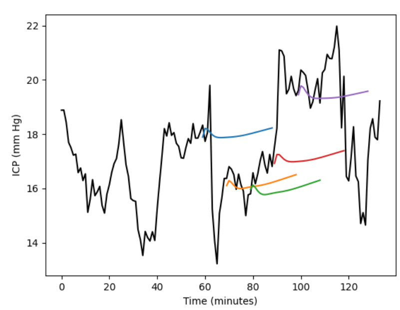

Fig. 2. 30-minute forecasts (LSTM).

Discussion: The MOMENT model was not very convenient to use. It only allowed one input feature with a fixed input window (512). This means that in many cases, zero padding needs to be used. The training (fine-tuning) of the MOMENT model is also slow compared to the LSTM.

We conclude this work by noting that based on our research, ICP forecasting based solely on the signal does not achieve sufficient performance for practical implementation. The concept of incorporating prior information into a model has a strong theoretical advantage, which was only partially realized in this study.

References

1. Nino Stocchetti and Andrew I.R. Maas. Traumatic Intracranial Hypertension. *New England Journal of Medicine*, 370(22):2121–2130, May 2014.
2. D. James Cooper, Jeffrey V. Rosenfeld, Lynnette Murray, Yaseen M. Arabi, Andrew R. Davies, Paul D'Urso, Thomas Kossmann, Jennie Ponsford, Ian Seppelt, Peter Reilly, and Rory Wolfe. Decompressive Craniectomy in Diffuse Traumatic Brain Injury. *New England Journal of Medicine*, 364(16):1493–1502, April 2011.
3. Peter J. Hutchinson, Angelos G. Kolias, Ivan S. Timofeev, Elizabeth A. Corteen, Marek Czosnyka, Jake Timothy, Ian Anderson, Diederik O. Bulters, Antonio Belli, C. Andrew Eynon, John Wadley, A. David Mendelow, Patrick M. Mitchell, Mark H. Wilson, Giles Critchley, Juan Sahuquillo, Andreas Unterberg, Franco Servadei, Graham M. Teasdale, John D. Pickard, David K. Menon, Gordon D. Murray, and Peter J. Kirkpatrick. Trial of Decompressive Craniectomy for Traumatic Intracranial Hypertension. *New England Journal of Medicine*, 375(12):1119–1130, September 2016.
4. Guochang Ye, Vignesh Balasubramanian, John K-J. Li, and Mehmet Kaya. Machine Learning-Based Continuous Intracranial Pressure Prediction for Traumatic Injury Patients. *IEEE Journal of Translational Engineering in Health and Medicine*, 10:1–8, 2022. Conference Name: IEEE Journal of Translational Engineering in Health and Medicine.
5. Akram Farhadi, Joshua J. Chern, Daniel Hirsh, Tod Davis, Mingyoung Jo, Frederick Maier, and Khaled Rasheed. Intracranial Pressure Forecasting in Children Using Dynamic Averaging of Time Series Data. *Forecasting*, 1(1):47–58, December 2019. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute.
6. Bin Han, Michael Muma, Mengling Feng, and Abdelhak M. Zoubir. An online approach for intracranial pressure forecasting based on signal decomposition and robust statistics. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 6239–6243, May 2013. ISSN: 2379-190X.
7. Sebastian Thrun and Tom M. Mitchell. Lifelong robot learning. *Robotics and Autonomous Systems*, 15(1):25–46, July 1995.
8. Venessa L. Pinto, Prasanna Tadi, and Adebayo Adeyinka. Increased Intracranial Pressure. In *StatPearls*. StatPearls Publishing, Treasure Island (FL), 2024.
9. Robert McNamara, Shiv Meka, James Anstey, Daniel Fatovich, Luke Haseler, Toby Jeffcote, Andrew Udy, Rinaldo Bellomo, and Melinda Fitzgerald. Development of Traumatic Brain Injury Associated Intracranial Hypertension Prediction Algorithms: A Narrative Review. *Journal of Neurotrauma*, 40(5-6):416–434, March 2023.
10. Charles C. Holt. Forecasting seasonals and trends by exponentially weighted moving averages. *International Journal of Forecasting*, 20(1):5–10, 1957.
11. Jeffrey L. Elman. Finding Structure in Time. *Cognitive Science*, 14(2):179–211, 1990. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1207/s15516709cog1402_1.
12. Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, November 1997. Conference Name: Neural Computation.
13. Mononito Goswami, Konrad Szafer, Arjun Choudhry, Yifu Cai, Shuo Li, and Artur Dubrawski. MOMENT: A Family of Open Time-series Foundation Models, May 2024. arXiv:2402.03885 [cs].