Personalized Blood Pressure Management After Endovascular Thrombectomy in Large Vessel Occlusion Stroke

Presented at the International Stroke Conference (ISC), 2026

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I. Background

Large vessel occlusion (LVO) accounts for over half of the deaths and severe disabilities in ischemic stroke. Endovascular thrombectomy (EVT) effectively restores vessel patency, yet nearly half of patients still experience poor outcomes, partly due to post-EVT management. Current blood pressure (BP) guidelines are overly generalized, lacking consideration of individual characteristics and dynamic physiological changes. This study aims to develop an AI-driven model to predict post-EVT outcomes based on patient characteristics, temporal dynamics, and BP control, enabling personalized BP management to improve recovery.

II. Methods

We collected data from 662 patients with LVO treated with EVT at Emory University Hospital between 2014 and 2023 to predict post-EVT outcomes (mRS$\leq$2 vs. $>$2). Data were stratified by patient into training (60%), validation (20%), and test (20%) sets. We set 8 consultation points (T_i = 8/16/.../64h post-ICU admission) and 4 BP adjustment windows (T_w = 2/4/6/8h), creating up to 32 data samples per patient (19,246 total samples). For each sample, three kinds of features were extracted: (i) pre-ICU features such as age, sex, and TICI; (ii) ICU temporal features derived from dynamic variables (e.g., MAP, SBP) up to T_i; (iii) BP target features representing T_w time window length and percentage. The three feature sets were processed using a three-branch multimodal prediction model. Linear encoders handled pre-ICU and BP features, while an LSTM processed ICU temporal features. The resulting embeddings were combined and fed into a classifier for prediction. The model was trained using ReLU activation, focal loss (alpha=0.25), Adam optimization (learning rate=1e-5, weight decay=0.01), and early stopping for 100 epochs.

III. Results

Our prediction model achieved the best performance across all evaluation metrics, demonstrating the effectiveness of integrating patient static, temporal dynamics, and BP target features. Compared with baselines, removing any feature group degraded performance, underscoring their complementarity. We further quantified how predicted outcomes vary with consultation time and optimal BP ranges to guide post-EVT management.

IV. Conclusion

We develop an AI model to predict post-EVT outcomes based on patient characteristics, temporal factors, and BP control, and to personalize BP management to improve recovery.

Variable	mRS≤2 (n=154)	mRS>2 (n=508)
Age (yrs)	61.0 [49.5,69.0]	68.0 [56.8,78.0]
BMI	29.1 [25.7,33.5]	28.6 [24.4,33.8]
Sex (M/F)	94/60	253/255
Race (B/W/A/O/U)	77/54/7/3/13	233/193/20/6/56
Ethnicity (H/NH/U)	10/122/22	8/424/76
TICI (3/2/1/0/U)	107/47/0/0/0	247/230/5/17/9
Site of Occlusion (ICA/MCA/BA/Other)	28/120/11/2	93/386/47/6
HT (Y/N)	Y: 0, N: 154	Y: 33, N: 475
Initial NIHSS	11.0 [6.0,17.0]	17.0 [12.0,22.0]
InHospMort (Y/N)	Y: 0, N: 154	Y: 51, N: 457

Fig. 1. Statistics of patient characteristics.

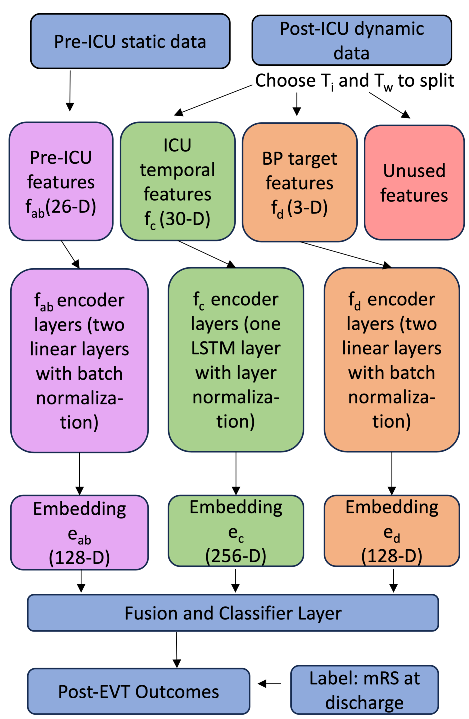

Fig. 2. Our prediction framework integrating pre-ICU static, ICU temporal, and BP target features through separate encoders, followed by fusion and classification layers to predict post-EVT outcomes.

(a)

Method	AUROC	ACC	F1	P	R
Full features (Ours)	**0.729±0.020**	**0.703±0.014**	**0.720±0.009**	**0.753±0.014**	**0.703±0.014**
No ICU dynamics	0.663±0.008	0.666±0.043	0.687±0.035	0.726±0.013	0.666±0.043
No BP target	0.720±0.030	0.692±0.016	0.710±0.014	0.746±0.019	0.692±0.016
No pre-ICU data	0.608±0.037	0.642±0.031	0.662±0.027	0.693±0.022	0.642±0.031

(b)

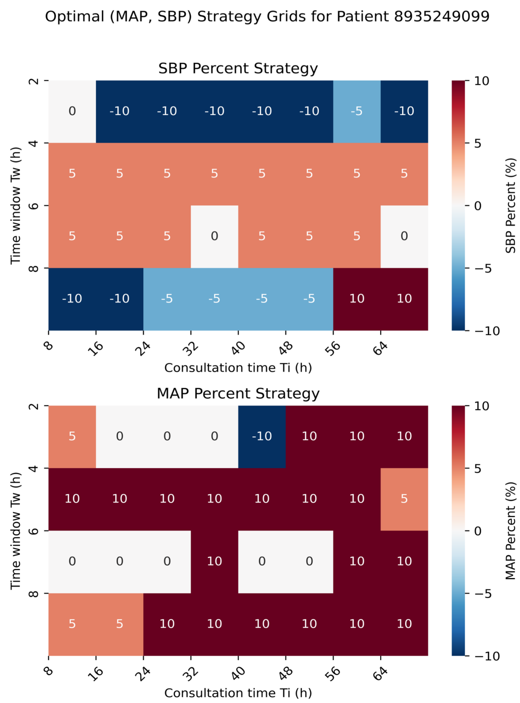

Fig. 3. Experimental results and case study. (a) Performance comparison showing the impact of ICU dynamics, BP targets, and pre-ICU data. (b) Optimal MAP/SBP adjustment strategies across consultation times and time window for one representative patient.