Supplementary

Appendix 1 Automated ROI segmentation with nnU-Net

For the segmentation task, nnU-Net, an open-source extension of the original U-Net architecture, was selected as the framework to identify and segment ROI. nnU-Net provides a comprehensive and automated solution, encompassing the entire segmentation pipeline, including preprocessing, data augmentation, model training, and post-processing. Therefore, we did not make any significant modifications to the default settings provided by nnU-Net, but directly adopted its automated processing flow. It is worth noting that all annotated images were used for model training to ensure that the model can learn the features and patterns of the hematoma area. The inference experiment used unlabeled images to verify the model's generalization ability on unknown data.

Appendix 2 Multivariate support vector regression for lesion-symptom mapping methods

After segmenting the ICH lesions, we normalized the segmented lesion mask to the CT template space using the Clinical Toolbox in SPM12 (45). This toolbox is specifically designed for spatial normalization of CT and MR brain images in elderly stroke populations, ensuring accurate registration of the lesion masks to the template space. Subsequently, we performed multivariate support vector regression for lesion-symptom mapping (SVR-LSM) analysis using a MATLAB-based toolbox (46). Unlike traditional voxel-wise analysis, SVR-LSM employs a nonlinear function to describe the symptom associations across the lesion map, considering the correlation between voxels. This approach provides a more comprehensive understanding of the associations between ICH locations and PSE, capturing spatial relationships between voxels rather than modeling each voxel individually. For the SVR-LSM analysis, we included all voxels that were damaged in at least 5 patients, leading to the exclusion of some subjects from the analysis (47).

Appendix 3 The process of evaluating the importance of random forest features

(I) Build model: Firstly, a model is constructed using the random forest algorithm, which consists of multiple decision trees.
(II) Assessment contribution: this process typically involves calculating the average reduction in impurity (such as Gini coefficient, entropy, etc.) of each feature during decision tree node splitting. The more impurity is reduced, the more important the feature is.
(III) Normalization: in order to compare the relative importance between different features, the evaluated feature importance values are normalized so that they are on the same scale.
(IV) Result explanation: finally, based on the normalized feature importance values, it is possible to intuitively understand which features have the greatest impact on the model's prediction results.

References

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Table S1 Post-stroke epilepsy screening questionnaire (24)

Q1: Self-reported diagnosis:
a. Has ever been diagnosed by a doctor to have seizures/epilepsies/convulsions after discharge? a
b. How soon after discharge did you experience the first recurrent seizure? b
Only patients responded Q1a with "yes" were recorded as post-stroke epilepsy, if not, patients were asked by following questions.
Q2: Symptom-based screening questions: a, b
a. Have you ever had, or has anyone told you that you had any of the following symptom after discharge? c
i. A seizure, convulsive, fit or spell under any circumstances?
ii. Uncontrolled movement of part or all of your body such as twitching, jerking, shaking, or going limp?
iii. An unexplained change in your mental state or level or unawareness; or an episode of "spacing out" that you could not control?
iv. Shortly after waking up, either in the morning or after a nap, have you ever noticed uncontrollable jerking or clumsiness, such as dropping things or things suddenly "flying" from your hands?
v. Have you ever had repeated unusual spells?
b. How soon after discharge did the symptom happen? b
Q3: Questions about anti-seizure medications?
a. Are you currently using any anti-seizure drug including 'valproate', 'levetiracetam', 'carbamazepine', or 'oxcarbazepine'?
b. If not, when did you stop the drug? d
a: Acceptable answers to each of the questions include: "yes", "no", "possible", or "don't know".
b: Only if the patient or caregiver can provide the approximate date or we can obtain it from the medical records, he/she were included in analysis.
c: Patients were diagnosed with PSE only if they fulfill 1+2+3 or 1+4 of the following:
1. "yes" for Q2a-i or ii, 2. Provide an approximate date for Q2b, 3. "yes" for Q3a, 4. confirmed by medical records.
If they respond "no" for any of the questions, they were recorded as non-PSE. Otherwise, they're excluded from analysis to ensure the best accuracy of diagnosis.
d: An approximate year

PSE, post-stroke epilepsy.

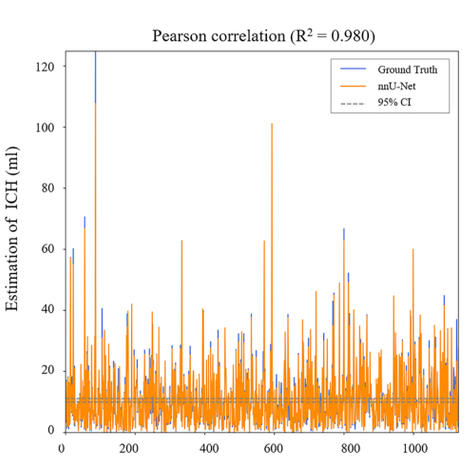

Figure S1 Correlation between the nnU-net determined ICH volumes and the ground truth. The high Pearson correlation coefficient (R^2=0.980) suggests a strong agreement between the nnU-Net model predictions and the actual ICH volumes. ICH, intracerebral hemorrhage; CI, confidence interval.

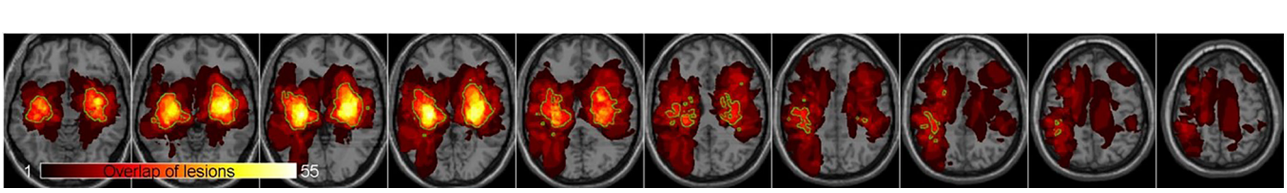

Figure S2 Overlay lesion maps of stroke lesions in PSE patients included in SVR-LSM (55 patients in total). For a more comprehensive view, the lesion maps were thresholded to include only voxels that were lesioned in at least 5 participants, showing the extensive coverage of temporal and frontal lobes. PSE, post-stroke epilepsy; SVR-LSM, support vector regression lesion-symptom mapping.

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Table S2 Report for beta-map with AAL atlas

Index	atlas_name	Voxel number
3	Frontal_Sup_L	37 out of 28,915 voxels
4	Frontal_Sup_R	35 out of 32,089 voxels
5	Frontal_Sup_Orb_L	135 out of 7,654 voxels
6	Frontal_Sup_Orb_R	140 out of 7,859 voxels
7	Frontal_Mid_L	15 out of 38,722 voxels
8	Frontal_Mid_R	31 out of 40,374 voxels
9	Frontal_Mid_Orb_L	192 out of 7,112 voxels
10	Frontal_Mid_Orb_R	220 out of 8,057 voxels
11	Frontal_Inf_Oper_L	16 out of 8,271 voxels
12	Frontal_Inf_Oper_R	13 out of 11,174 voxels
13	Frontal_Inf_Tri_L	5 out of 20,104 voxels
15	Frontal_Inf_Orb_L	185 out of 13,590 voxels
16	Frontal_Inf_Orb_R	207 out of 13,747 voxels
17	Rolandic_Oper_L	4 out of 7,939 voxels
18	Rolandic_Oper_R	21 out of 10,733 voxels
21	Olfactory_L	19 out of 2,262 voxels
22	Olfactory_R	16 out of 2,286 voxels
23	Frontal_Sup_Medial_L	39 out of 23,852 voxels
24	Frontal_Sup_Medial_R	41 out of 16,979 voxels
25	Frontal_Med_Orb_L	125 out of 5,792 voxels
26	Frontal_Med_Orb_R	130 out of 6,870 voxels
27	Rectus_L	94 out of 6,864 voxels
28	Rectus_R	99 out of 5,930 voxels
29	Insula_L	87 out of 15,025 voxels
30	Insula_R	86 out of 14,128 voxels
31	Cingulum_Ant_L	2 out of 11,289 voxels
36	Cingulum_Post_R	5 out of 2,654 voxels
37	Hippocampus_L	104 out of 7,469 voxels
38	Hippocampus_R	82 out of 7,606 voxels
39	ParaHippocampal_L	60 out of 7,891 voxels
40	ParaHippocampal_R	74 out of 9,028 voxels
41	Amygdala_L	11 out of 1,733 voxels
42	Amygdala_R	26 out of 1,965 voxels
43	Calcarine_L	70 out of 18,157 voxels
44	Calcarine_R	38 out of 14,885 voxels
45	Cuneus_L	2 out of 12,133 voxels
46	Cuneus_R	4 out of 11,323 voxels
47	Lingual_L	210 out of 16,932 voxels
48	Lingual_R	205 out of 18,450 voxels
49	Occipital_Sup_L	7 out of 10,791 voxels
50	Occipital_Sup_R	4 out of 11,149 voxels
51	Occipital_Mid_L	51 out of 25,989 voxels
52	Occipital_Mid_R	12 out of 16,512 voxels
53	Occipital_Inf_L	54 out of 7,536 voxels
54	Occipital_Inf_R	72 out of 7,929 voxels
55	Fusiform_L	227 out of 18,333 voxels
56	Fusiform_R	269 out of 20,227 voxels
67	Precuneus_L	8 out of 28,358 voxels
68	Precuneus_R	6 out of 26,083 voxels
71	Caudate_L	26 out of 7,682 voxels
72	Caudate_R	22 out of 7,941 voxels
73	Putamen_L	110 out of 7,942 voxels
74	Putamen_R	86 out of 8,510 voxels
75	Pallidum_L	44 out of 2,285 voxels
76	Pallidum_R	65 out of 2,188 voxels
81	Temporal_Sup_L	143 out of 18,307 voxels
82	Temporal_Sup_R	149 out of 25,258 voxels
83	Temporal_Pole_Sup_L	152 out of 10,228 voxels
84	Temporal_Pole_Sup_R	180 out of 10,654 voxels
85	Temporal_Mid_L	303 out of 39,353 voxels
86	Temporal_Mid_R	281 out of 35,484 voxels
87	Temporal_Pole_Mid_L	85 out of 5,984 voxels
88	Temporal_Pole_Mid_R	119 out of 9,470 voxels
89	Temporal_Inf_L	315 out of 25,647 voxels
90	Temporal_Inf_R	383 out of 28,468 voxels
91	Cerebelum_Crus1_L	242 out of 20,667 voxels
92	Cerebelum_Crus1_R	219 out of 21,017 voxels
93	Cerebelum_Crus2_L	30 out of 15,216 voxels
94	Cerebelum_Crus2_R	32 out of 17,038 voxels
95	Cerebelum_3_L	19 out of 1,072 voxels
96	Cerebelum_3_R	26 out of 1,600 voxels
97	Cerebelum_4_5_L	110 out of 9,034 voxels
98	Cerebelum_4_5_R	95 out of 6,763 voxels
99	Cerebelum_6_L	174 out of 13,672 voxels
100	Cerebelum_6_R	172 out of 14,362 voxels
101	Cerebelum_7b_L	4 out of 4,639 voxels
102	Cerebelum_7b_R	14 out of 4,230 voxels
103	Cerebelum_8_L	10 out of 15,090 voxels
104	Cerebelum_8_R	10 out of 18,345 voxels
105	Cerebelum_9_L	26 out of 6,924 voxels
106	Cerebelum_9_R	20 out of 6,462 voxels
110	Vermis_3	10 out of 1,822 voxels
111	Vermis_4_5	135 out of 5,324 voxels
112	Vermis_6	50 out of 2,956 voxels
113	Vermis_7	5 out of 1,564 voxels
114	Vermis_8	1 out of 1,940 voxels
115	Vermis_9	12 out of 1,367 voxels
116	Vermis_10	16 out of 874 voxels

AAL, anatomical automatic labeling.

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