End-to-End Stroke Imaging Analysis Using Effective Connectivity and Interpretable Artificial Intelligence

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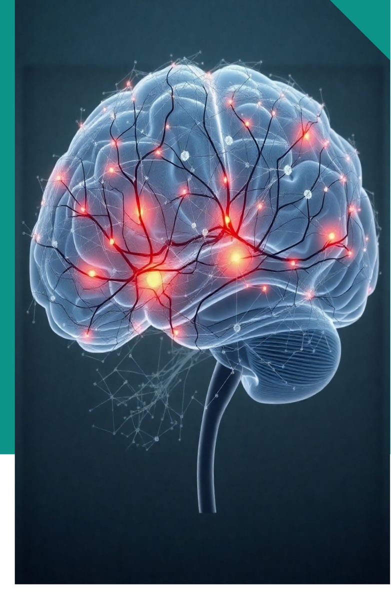
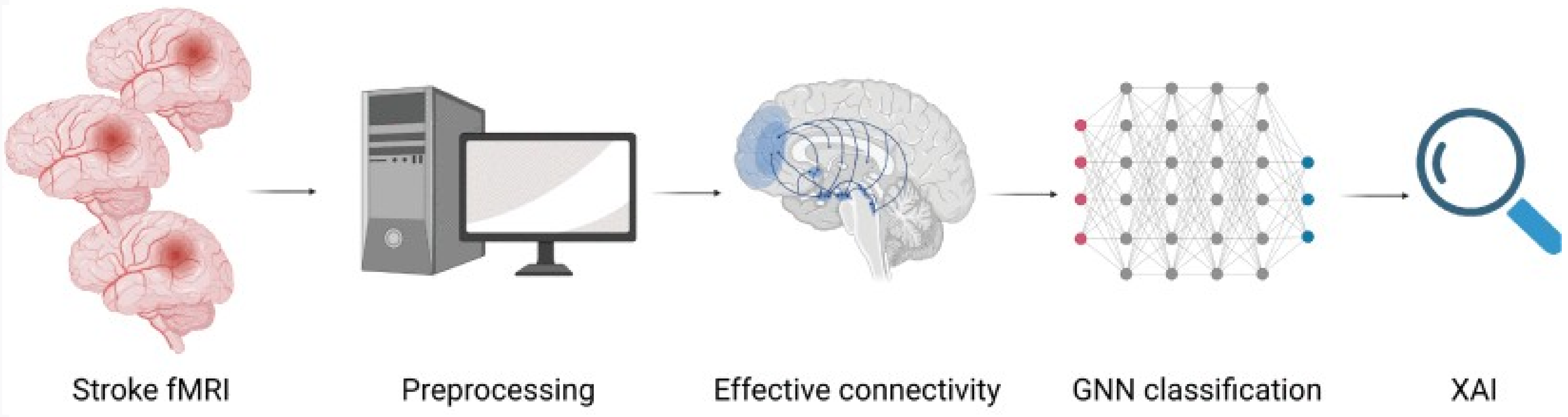
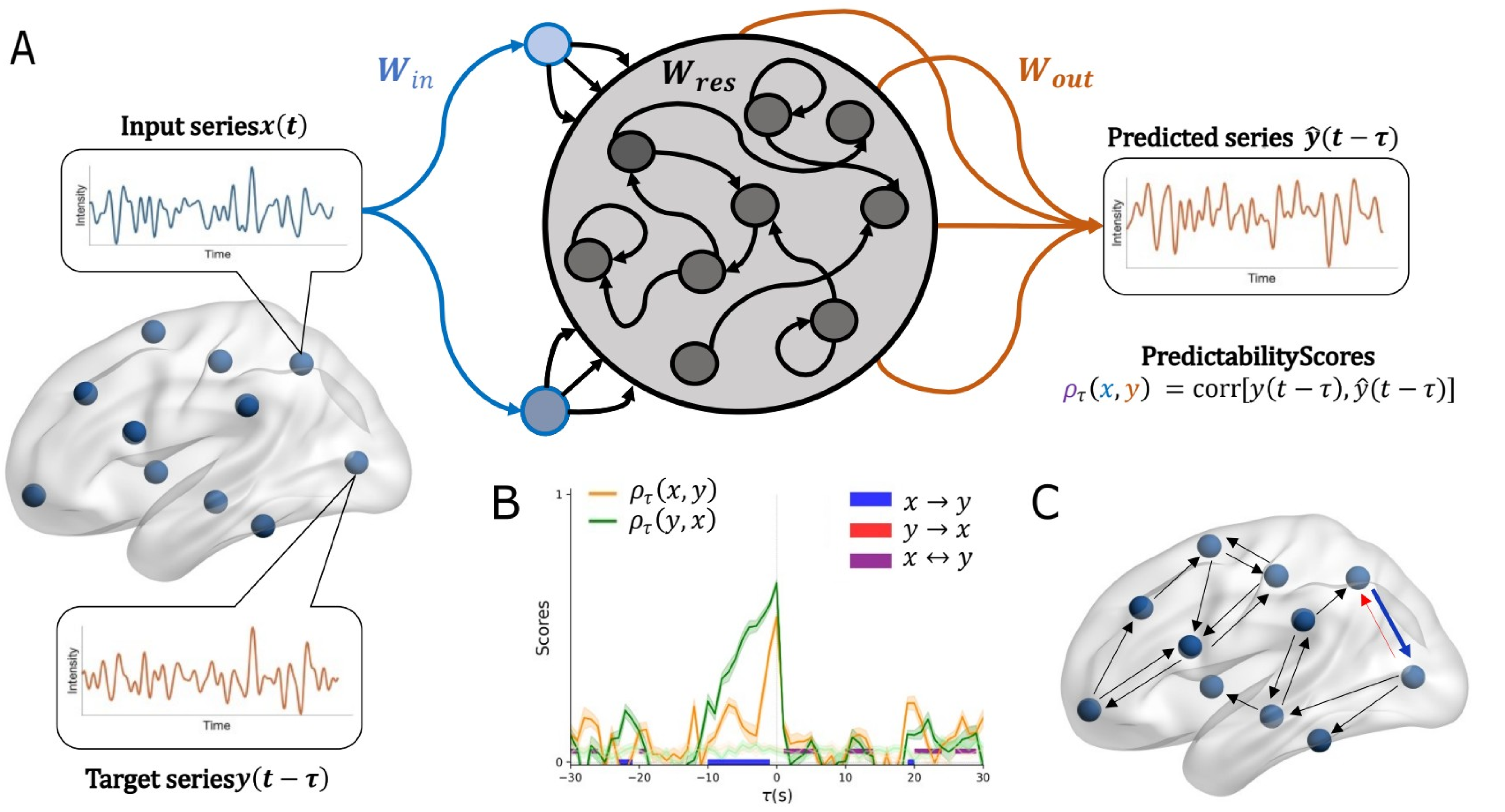


Background

- Stroke disrupts brain communication; effective connectivity offers directed measures capturing causal influence between brain regions.
- Existing stroke MRI analysis lacks approaches those miscommunication
- This work fills the gap by applying reservoir computing-based nonlinear effective connectivity and explainable AI methods for stroke detection and interpretation.
- Objective: To develop an end-to-end pipeline from MRI analysis through effective connectivity estimation, graph classification, and interpretable AI to identify and explain stroke-related brain network disruptions.

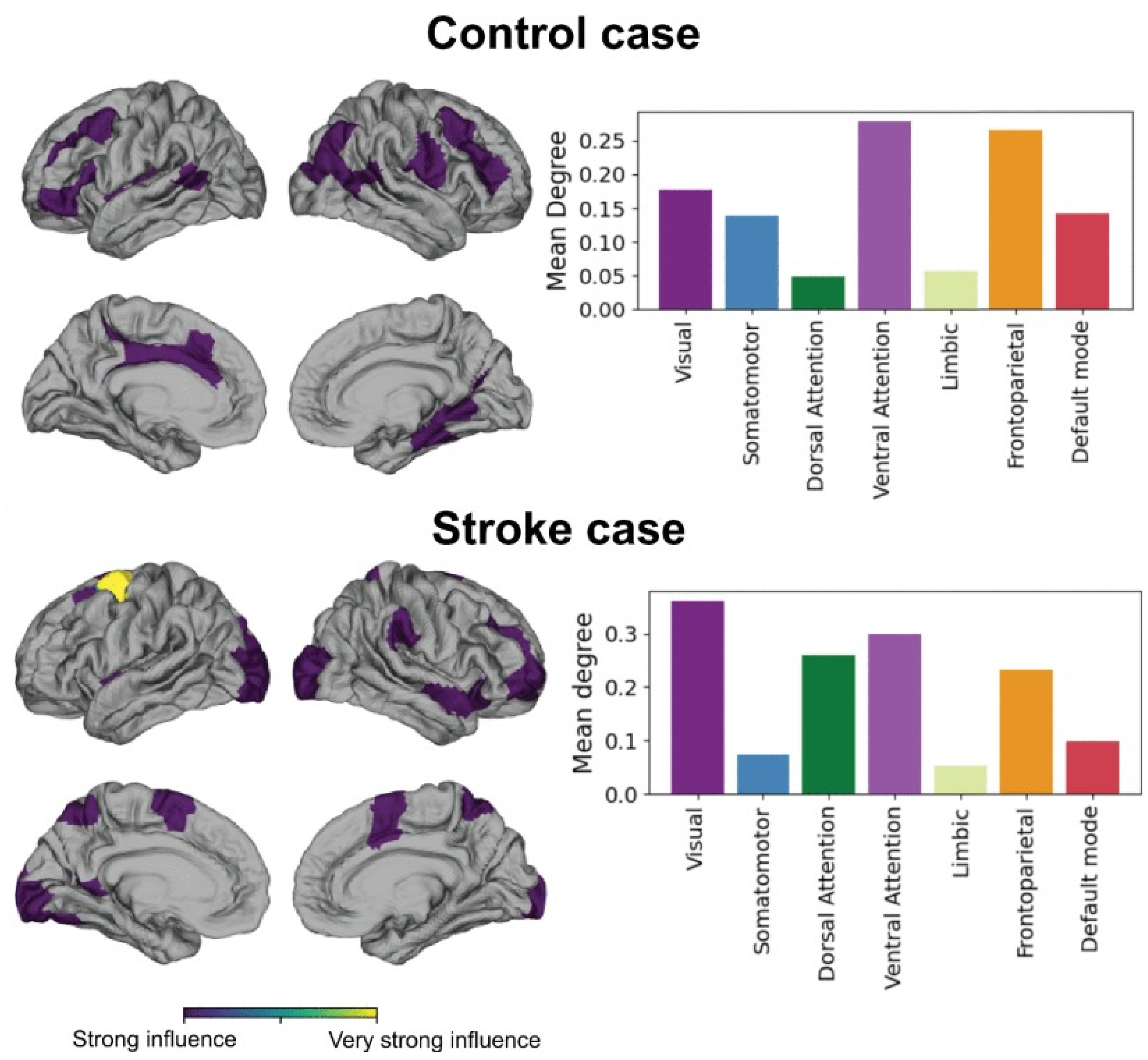




Reservoir computing causality: Nonlinear recurrent network embedding temporal dynamics.

Methods

- Data comprised fMRI from 104 acute stroke patients and 26 controls; preprocessed, and averaged according to the Schaefer atlas (100).
- Effective connectivity estimation used three methods: Granger causality, transfer entropy, and **reservoir computing causality.**
- Connectivity matrices were mean-centered by control averages, thresholded, and binarized to reduce noise prior to classification.
- Classification models included graph convolutional neural networks (GNN), random forests leveraging local topology profiles, and support vector machines (SVM).
- Explainability utilized LIME to identify key contributing brain nodes and edges.



Results

Effective Connectivity Mapping

- Effective connectivity maps demonstrated hemispheric segregation and disruption of intra- and inter-hemispheric connectivity in stroke patients compared to controls, with more pronounced effects in right hemisphere strokes.
- Statistical testing (two-sample t-test, p = 0.05) confirmed significance of global connectivity differences as shown in Figure 4.

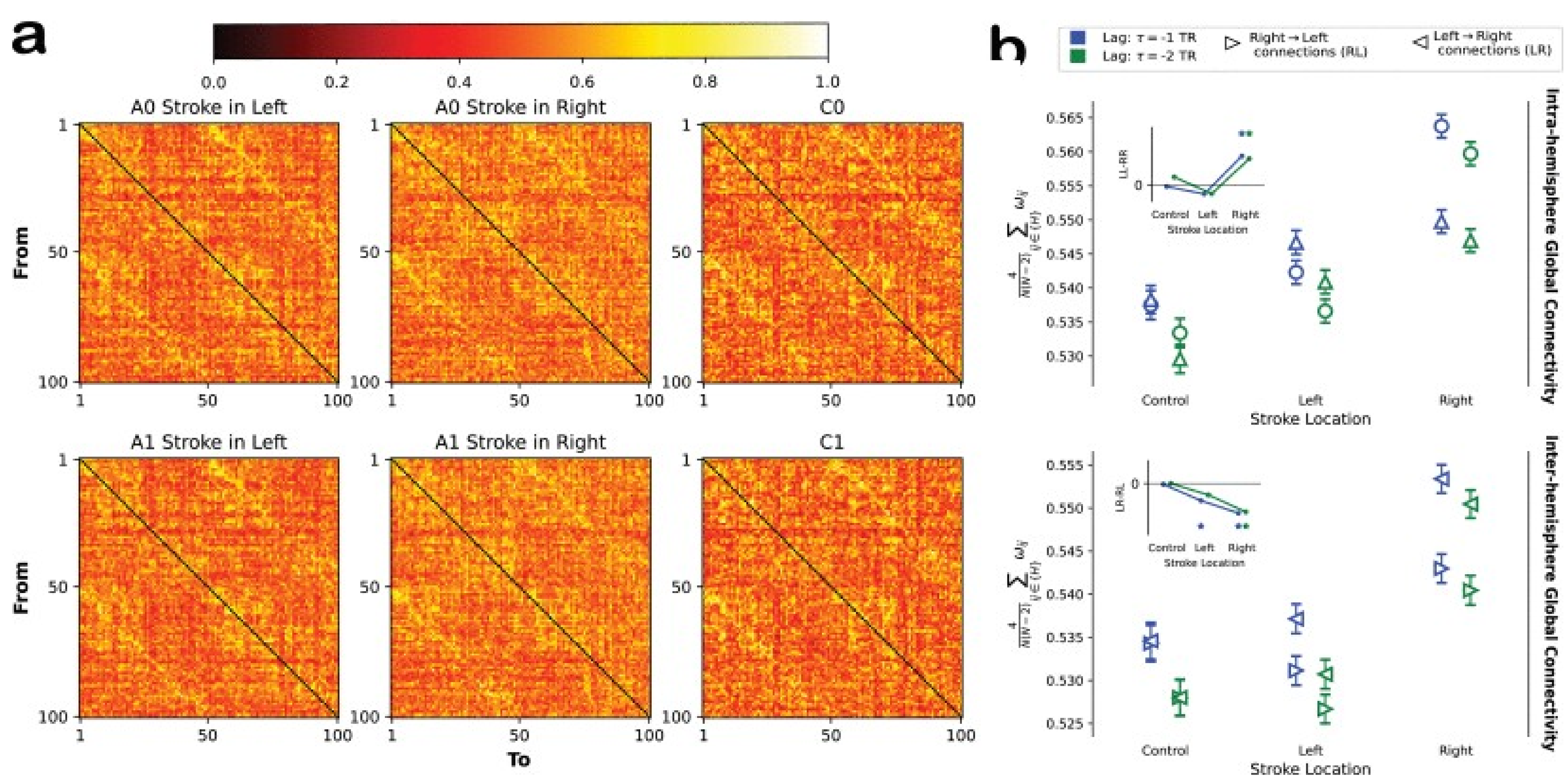
Classification Performance

- Graph convolutional neural networks (GNN) achieved moderate stroke detection AUCs: 0.6866 using reservoir computing causality and 0.6816 with Granger causality matrices. Random forest classifier showed improvements on various metrics with Granger causality features

Explainability of Stroke-Associated Networks

- LIME explainability highlighted brain regions such as visual, dorsal, and ventral attention networks as key discriminators for stroke detection.
- Ventral attention and frontoparietal networks were particularly important for classifying control subjects.

Metric	RCC	GC	Transfer Entropy
AUC score	0.6866 ± 0.0830	0.6074 ± 0.0588	0.6024 ± 0.0573
Accuracy	0.6816 ± 0.0551	0.5386 ± 0.1610	0.5251 ± 0.1708
Precision	0.9253 ± 0.0654	0.9178 ± 0.0585	0.9111 ± 0.0581
Recall	0.6870 ± 0.0991	0.4968 ± 0.2184	0.4799 ± 0.2071
F1 score	0.7808 ± 0.0511	0.6143 ± 0.1922	0.6037 ± 0.1881



Key Findings

- Stroke induces disrupted effective connectivity with pronounced hemispheric asymmetry, detectable via reservoir computing causality.
- Graph convolutional neural networks leveraging nonlinear RCC features achieve moderate acceptable classification accuracy).
- Explainability analysis localizes visual, dorsal, and ventral attention networks as key in stroke detection and characterization.
- Results support using nonlinear connectivity and interpretable AI for clinical stroke imaging and rehabilitation guidance.

“End-to-end stroke imaging analysis using effective connectivity and interpretable artificial intelligence”. W. Ciezobka, J. Falco-Roget, C., Koba, & A. Crimi IEEE Access 2025.

“Reshaped functional connectivity gradients in acute ischemic stroke” C Koba, J Falco-Roget, A Crimi, NeuroImage: Clinical 45 (2025), 103755