

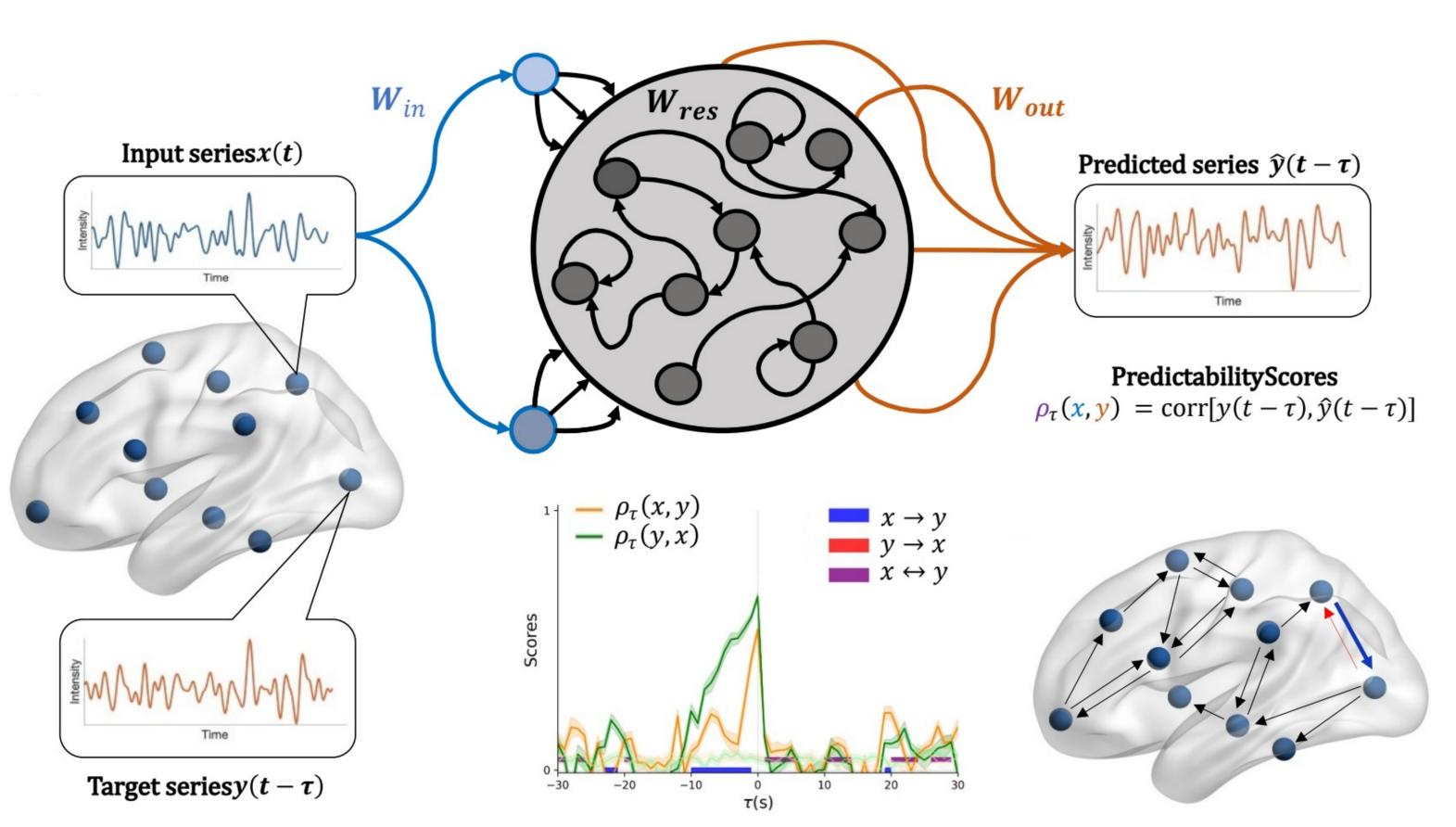
# End-to-End Stroke Imaging Analysis Using Effective Connectivity and Interpretable Artificial Intelligence

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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.

### Results

#### **Effective Connectivity Mapping**

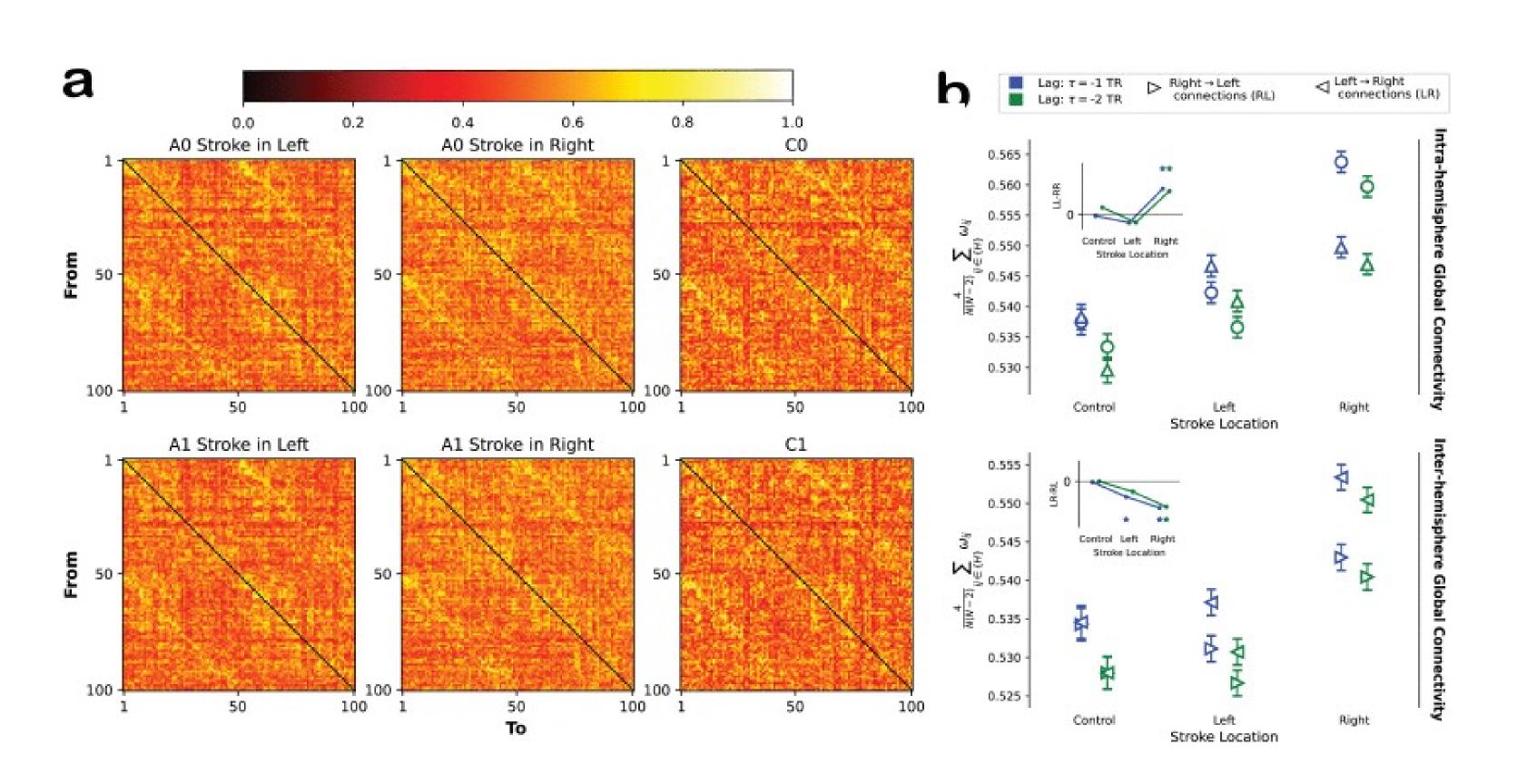
- Effective connectivity maps demonstrated hemispheric segregation and disruption of intra- and inter-hemispheric connectivity in stroke patients compared to controls, with more pronounced effects in right hemisphere strokes.
- Statistical testing (two-sample t-test, p = 0.05) confirmed significance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

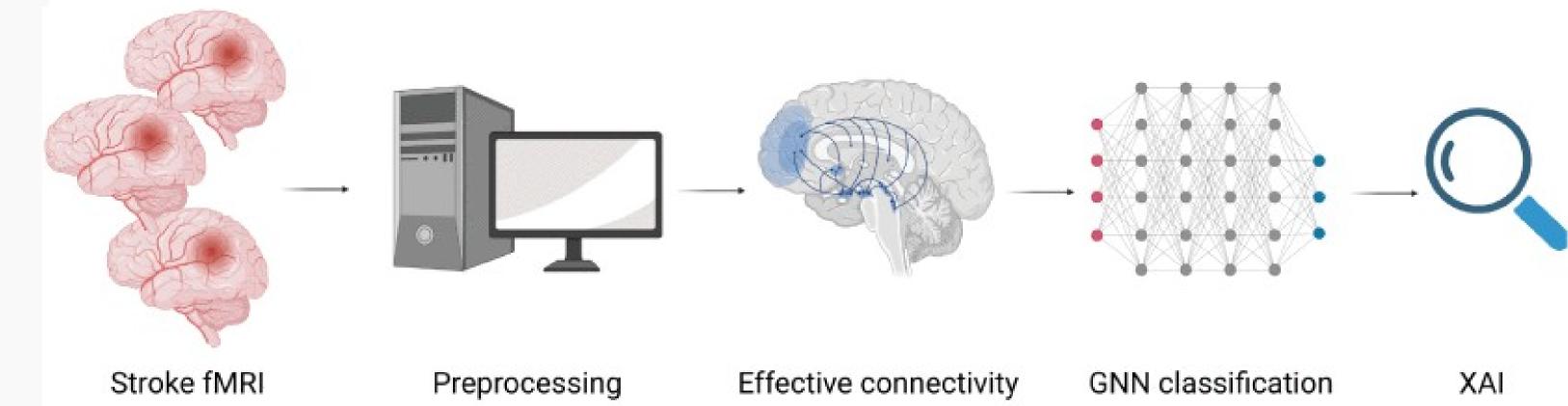
#### Classification Performance

- 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.





#### Methods

vector machines (SVM).

- -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
- -Explainability utilized LIME to identify key contributing brain nodes and edges.

# 

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

## 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.



