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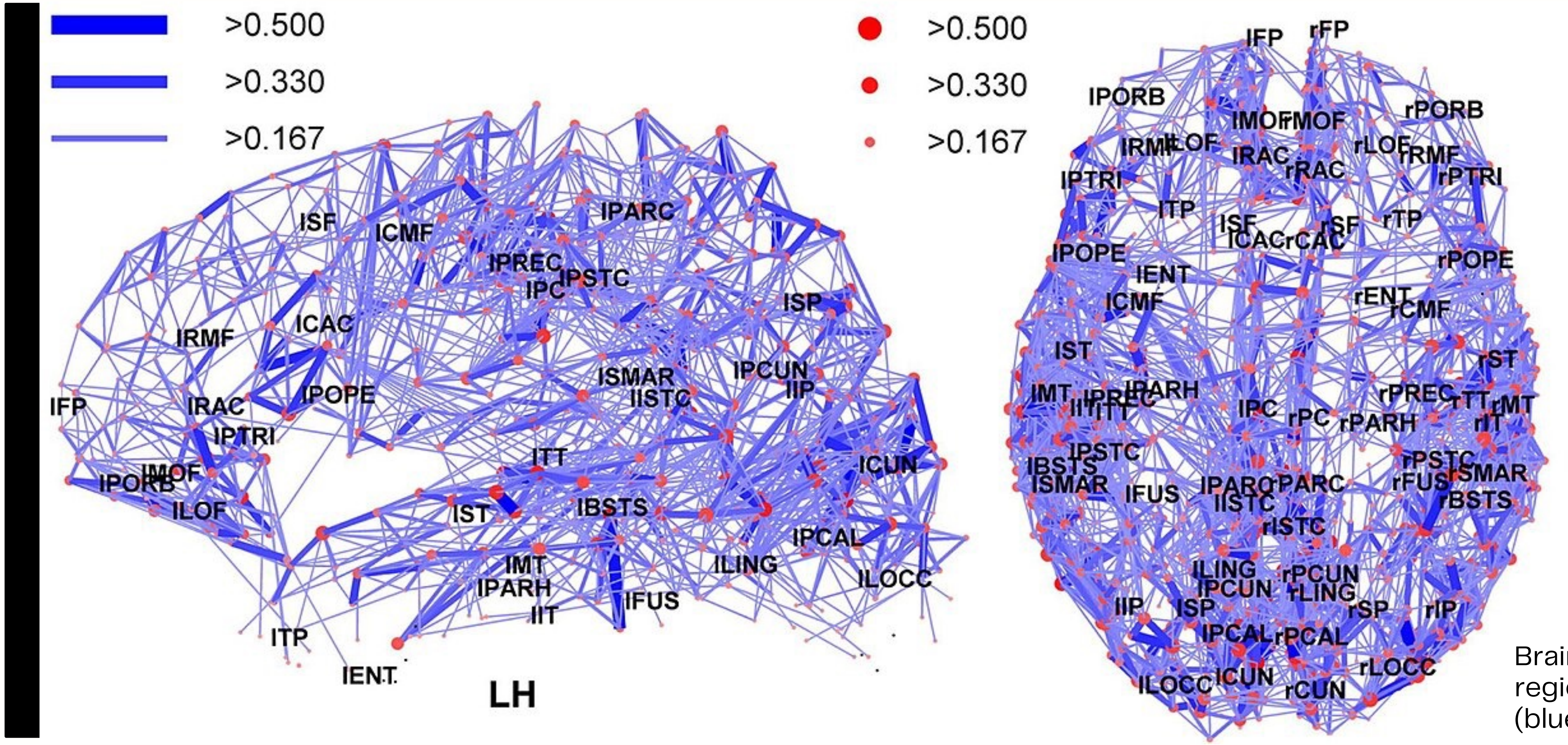


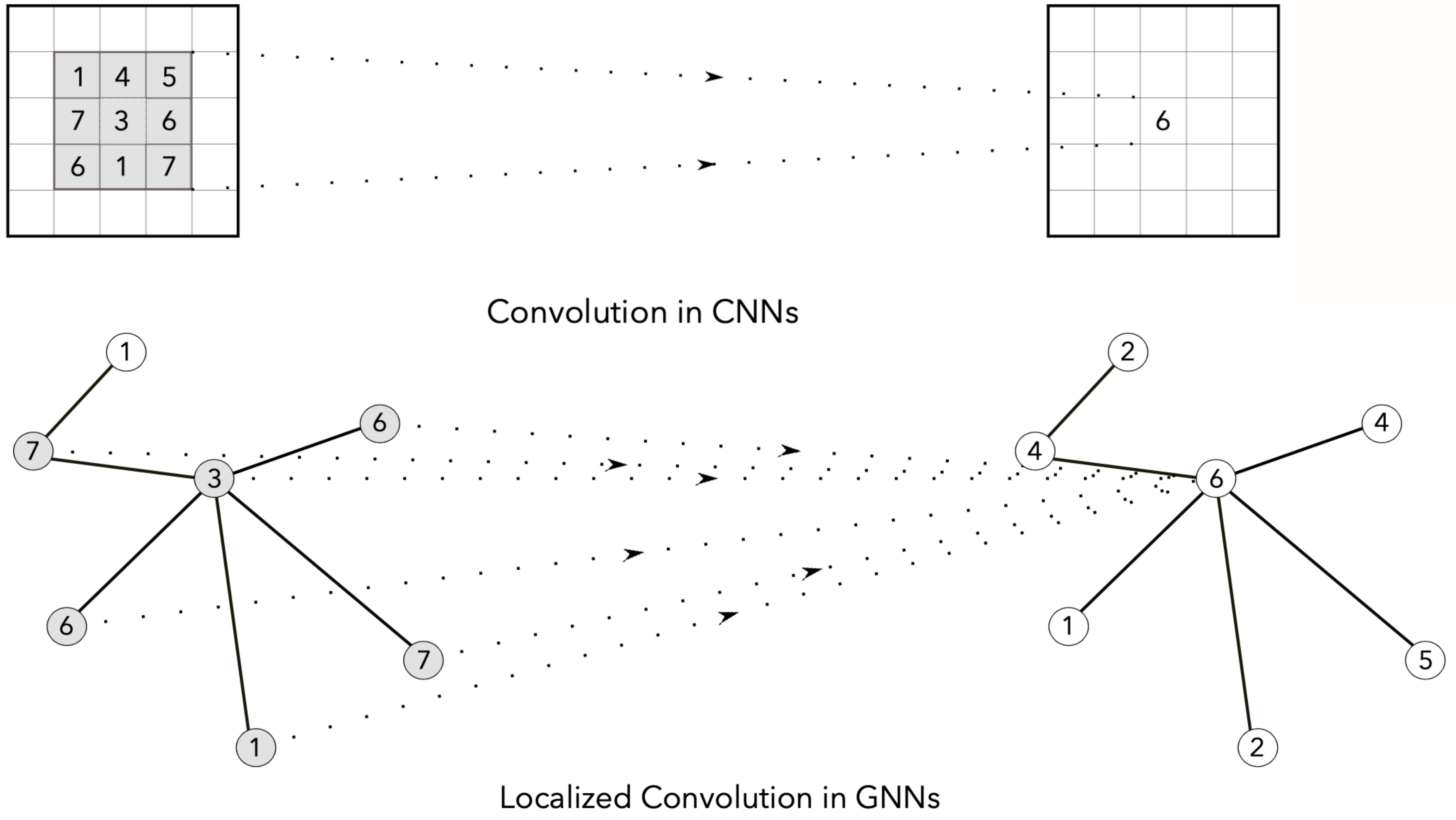
Brain connectivity graph. Each node – brain region (red points), edge – connection strength (blue lines). **(Hagmann et al., 2008)**

Graph Neural Network (GNN) : A Deep Learning Algorithm for Medical Image Analysis

Anastasiia Deviataieva

Introduction

Different methods of processing images . **(Wang et al., 2024)**



Top: classic CNN aggregates from a rigid 3 × 3 neighbourhood.
Bottom: GNN aggregates from each node's set of neighbours. **(Daigavane et al., 2021)**

- Medical anatomy = irregular, sparse, relational. Cells, lesions, vessels, regions rarely align to a rigid pixel grid
- CNNs: Local filters slide over fixed neighborhoods; good for textures, less flexible for irregular shapes & long-range structure
- ViTs: Flatten image into equal-sized patches; global attention but still patch-grid biased
- GNN: neural network that operates on graph-structured data (nodes & edges represent entities & relationships ↔ adjacency, interaction, co-activation) → better modeling of anatomical & functional networks

GNN Architecture – Message Passing

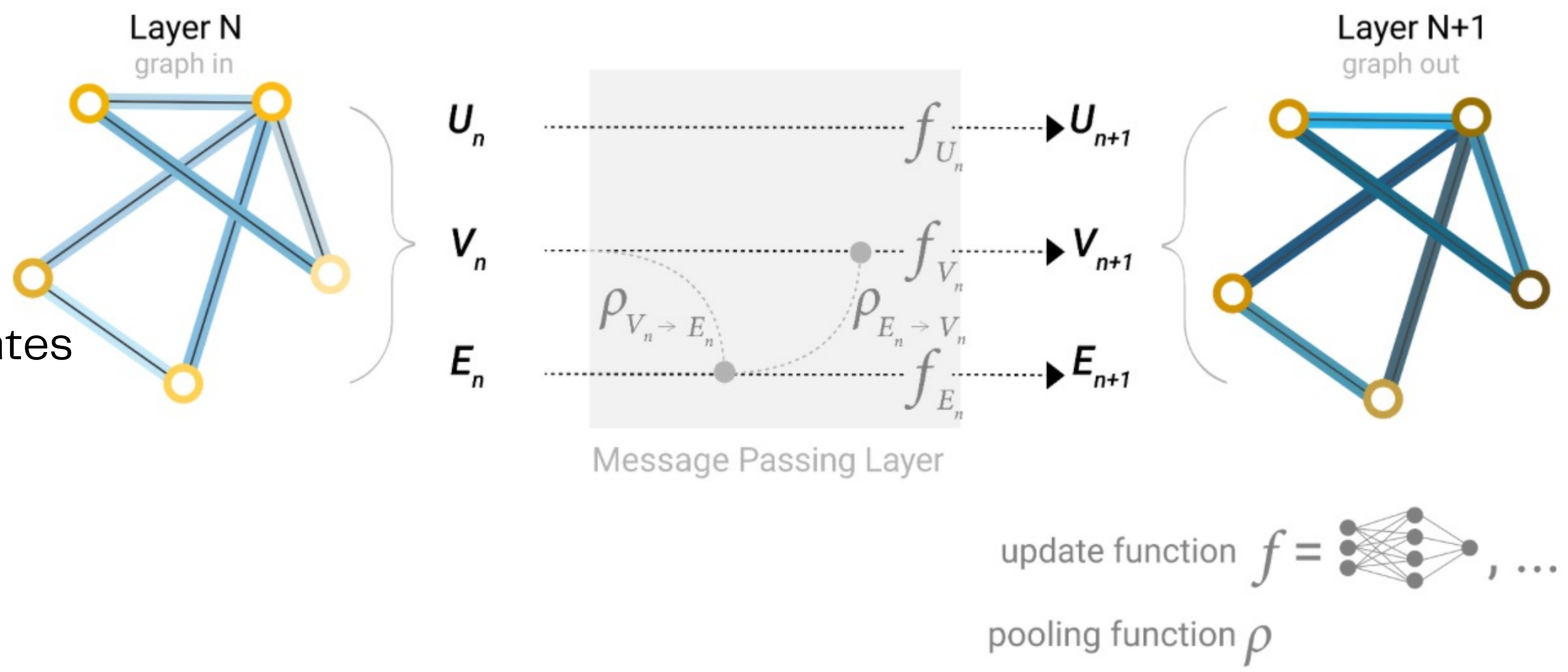
Node features: Each node starts with features (e.g. intensity, texture of a region)

Neighbors' influence: At each layer, a node aggregates feature information from its neighbors

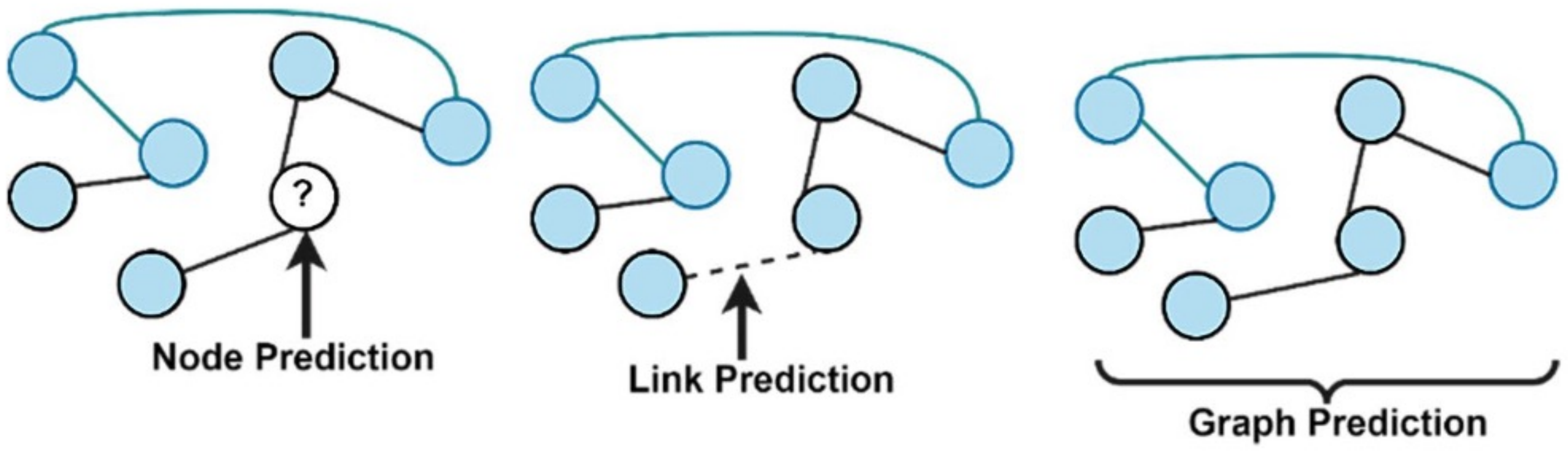
Update step: Node's own feature is updated via an update function (e.g. neural network) using aggregated neighbor

Iterative layers: Repeating this yields context-enriched node representations (captures local context)

Prediction Levels: node-level, edge-level, and graph-level tasks (e.g. classifying a cell, a connection, or an entire network)



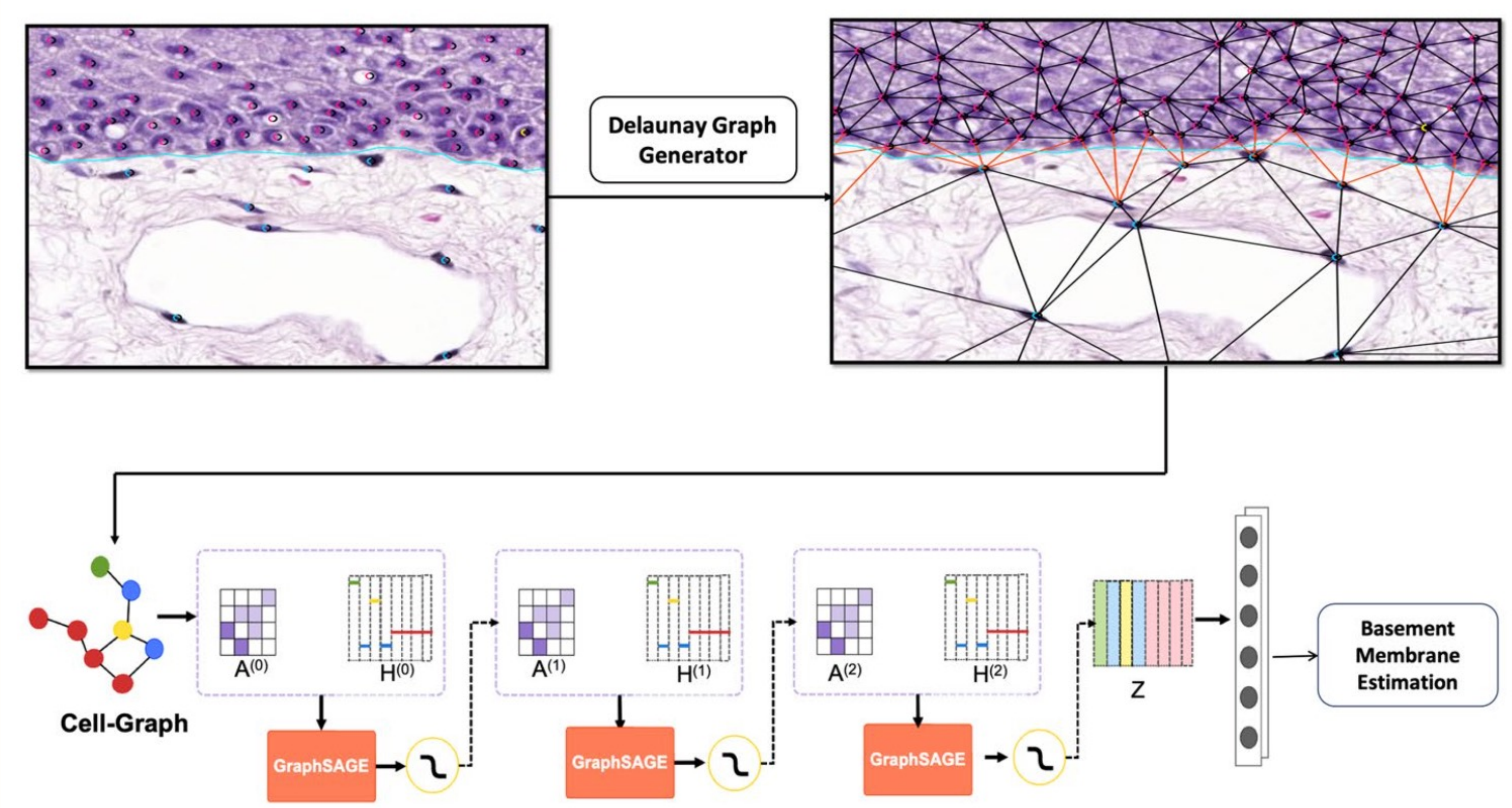
Message Passing structure **(Sanchez-Lengeling et al., 2021)**



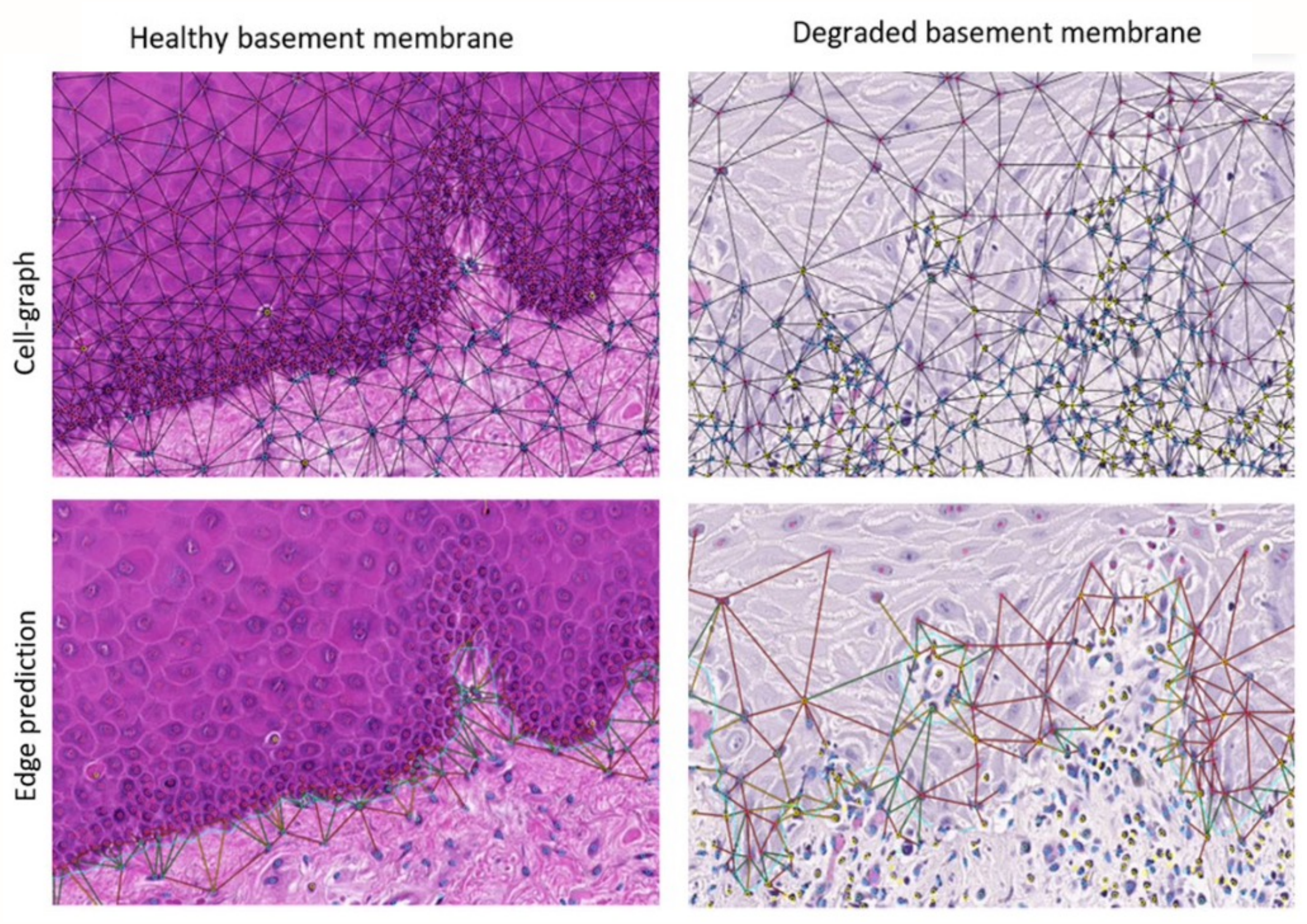
Prediction levels **(Khemani et al., 2024)**

Common GNN Variants

- GCN (Graph Convolutional Network): normalised mean of neighbor features → same weight for every neighbor.
- GAT(Graph Attention Network): learns an attention weight per edge → important neighbors contribute more.
- GraphSAGE (Graph Sample & Aggregate): samples a fixed-size neighbor set and aggregates (mean/max-pool/ LSTM); inductive—works on unseen nodes.



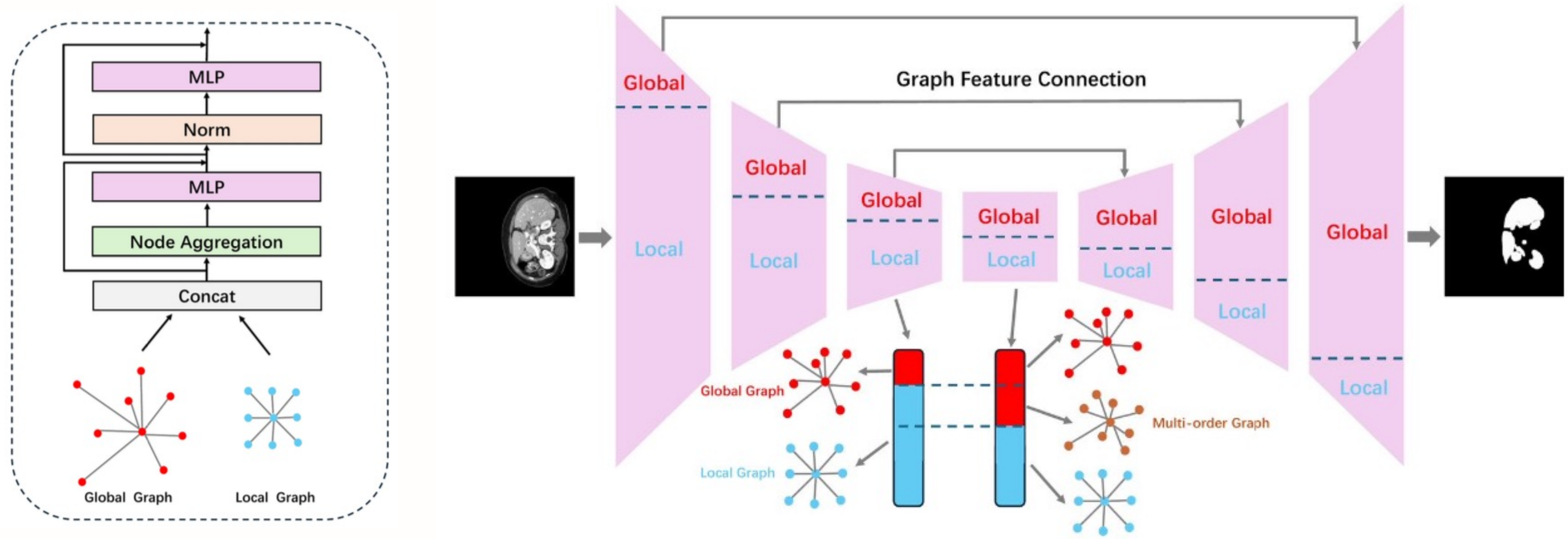
Training procedure for a GraphSage to identify the edges crossing the BM. **(Nair et al., 2022)**



Cell-graph over healthy vs. degraded basement membrane. **(Nair et al., 2022)**

Case study: U-GNN

- U-shaped encoder–decoder built entirely from Vision GNN blocks (no conv layers)
- Per block: build Local (adjacent patches) + Global (top-k similar) graphs → aggregate → MLP.
- Multi-order similarity: higher-order context “for free” via channel split.
- Skip connections: encoder detail fused back in the decoder.



U-GNN architecture: a Vision GNN block (left) and the U-shaped encoder–decoder with local/global graphs and skip connections (right) **(Xiao et al., 2025)**

U-GNN results

According to Xiao et al. (2025) U-GNN achieved:

- Superior accuracy
- Better tumour modelling
- Greater efficiency & robustness

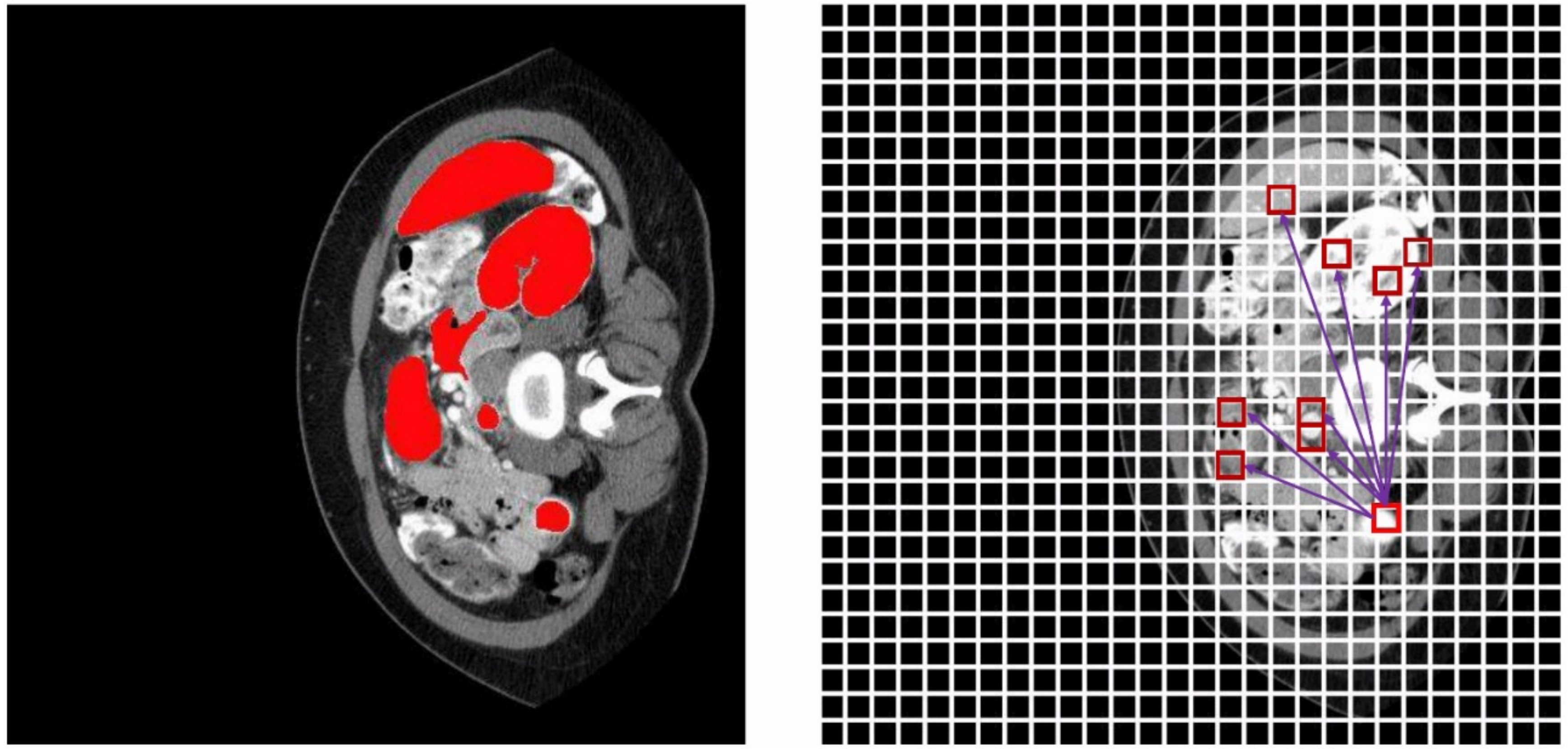
Methods	DSC	RV	Myo	LV
R50 U-Net	87.55	87.10	80.63	94.92
R50 Att-UNet	86.75	87.58	79.20	93.47
R50 ViT	87.57	86.07	81.88	94.75
TransUnet	87.57	86.07	81.88	94.75
SwinUnet	90.00	88.55	85.62	95.83
U-GNN	**91.53**	**89.87**	**87.26**	**96.51**

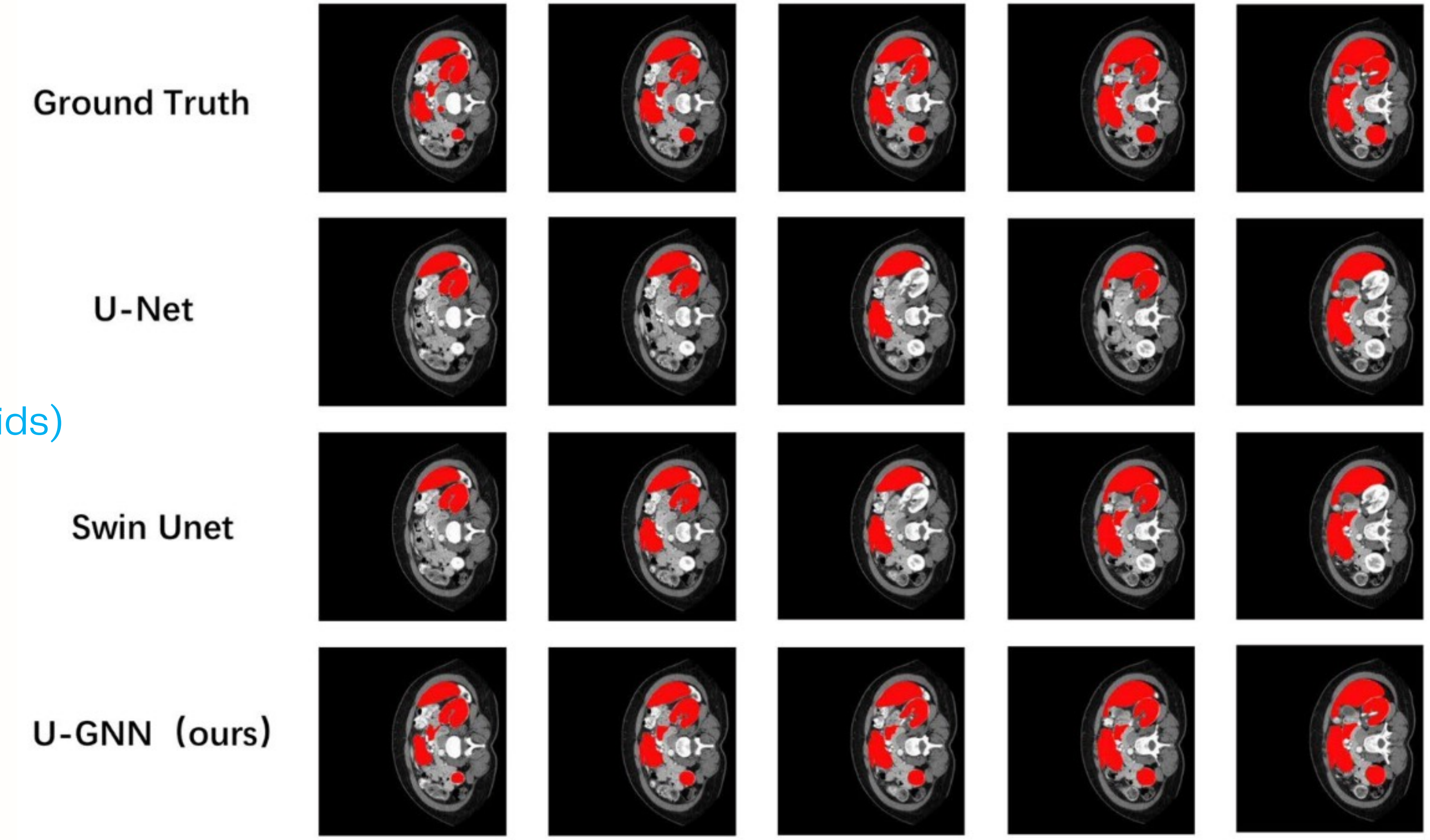
CNN based

ViT based (including hybrids)

Methods	Training Speed(it/s)↑	GPU memory occupancy(GB)↓
TransUnet	6.24	7.97
SwinUnet	6.59	7.73
U-GNN	**6.96**	**7.31**

Segmentation accuracy of different methods (top) Compute Efficiency results (bottom) **(Xiao et al., 2025)**





Interactions between tumour image patches and other image nodes within the model. (top) The segmentation results of different models (bottom) **(Xiao et al., 2025)**

Applications in Medical Imaging

- Segmentation (tumors, organs, vessels) (Xiao et al. (2025), Jiang et al. (2024), Mohammadi and Allali (2024))
- Classification / Grading / Prognosis (Brussee et al. (2025), Fu et al. (2024), Nair et al. (2022), Chowa et al. (2023))
- Detection & Localization & Anomaly QL (Zhao and Yin (2021), Nasser et al. (2024), Li et al. (2024))
- Registration & Motion Tracking (Zhou and Cao (2024), Rajesh et al. (2025), Sideri-Lampretsa et al. (2024))
- Multi-modal & Multi-scale Fusion & Reconstruction & Explainability (Mohammadi and Karwowski (2024), Fu et al. (2024), Chatterjee et al. (2025))

GenAI using reflection

GenAI: ChatGPT(OpenAI), models o3 and o4-mini-high + Deep Search

Cons:

- Shallow or vague explanations → I had to unpack the mechanics myself.
- GenAI outputs often have an overconfident tone + make occasional silly errors.
- Prompt sensitivity: a tiny wording change shifts depth and direction.
- Long/multi-step requests are only partially completed—must be split up.

Pros:

- Quickly gathered and filtered up-to-date literature, formatted it consistently, and track to avoid duplicates.
- Helped sketch the presentation's framework and logical sections.
- Suggested effective keywords and adjacent search terms.
- Rephrased complex articles' passages and smoothed the overall writing style.

Examples of GenAI prompts:

- Introduce Graph Neural Networks for medical image analysis by comparing them to Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs). Emphasize why medical images often have irregular, relational structures (cells, vessels, etc.) that CNNs (grid-based) and ViTs (patch-based) struggle with, and how GNNs operating on graphs can better capture these anatomical relationships.

- Explain the core architecture of a Graph Neural Network and the concept of message passing. Describe how each node in a graph has initial features and iteratively updates its state by aggregating information from neighboring nodes through multiple layers, and mention that GNNs can make predictions at the node level (e.g. classifying a cell), edge level (e.g. relationship between regions), or whole-graph level (e.g. outcome for an entire network).

- Present a case study of a U-shaped Graph Neural Network ("U-GNN") designed for medical image segmentation. Explain how this model replaces all CNN layers with GNN-based blocks in a U-Net style encoder–decoder, constructing local graphs (adjacent image patches) and global graphs (most similar patches) at each stage, and using skip connections to fuse low-level and high-level information. Also summarize the results reported for U-GNN: it outperformed standard CNN-based U-Nets and ViT-based models (like TransUnet, Swin-Unet), achieving higher tumor segmentation accuracy, better modeling of complex tumor shapes, and more efficiency (faster training and lower memory usage).

- Find and summarize 15 the most up-to-date, high-quality sources on Graph Neural Networks for Medical Image Analysis published from 2022 to present. Prioritize peer-reviewed papers, reputable medical AI surveys, and systematic reviews. For each source, provide: Full citation (authors, year, title, venue/journal); One-sentence key finding; Why it is relevant to segmentation, detection, or prognosis tasks in medical imaging; Type of study (benchmark, clinical validation, method, survey). Return the results in a markdown table with these columns: Rank | Citation | Year | Key Finding | Relevance | Study Type | Link/DOI. Exclude anything before 2022. If you can't find enough recent sources, note the gap and suggest me alternative keywords (e.g., 'vision GNN', 'cell graphs', 'pathology graphs'). After the table, add 3–4 bullets synthesizing major trends, limitations, and open problems. Use Harvard style for citations.

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THANK YOU!