A hierarchical geometry-to-semantic fusion GNN framework for earth surface anomalies detection

Boan Chen, Aohan Hu, Mengjie Xie,
Zhi Gao, Xuhui Zhao, and Han Yi

Speaker: Xuhui Zhao

武漢大學
WUHAN UNIVERSITY

NUS
National University of Singapore

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Outline

- **Background and Motivation**
- Method
- Experiments
- Conclusion and Future Work

Background and Motivation

- Various earth's surface anomalies caused by natural or human factors (natural disasters, ecological damage, etc.) occur on a global scale and are characterized by high frequency, high impact and heavy losses.
- Timely monitoring and early warning of earth surface anomalies has become a major need to ensure healthy and stable social and economic development.

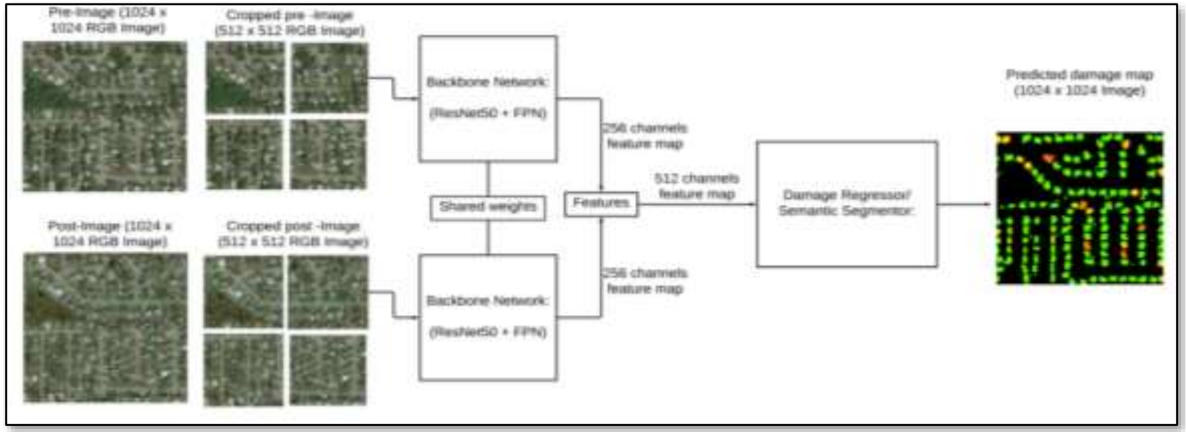
Background and Motivation

- Remote Sensing Detection
- Real-time, Large-scale, Non-contact, Dynamic, etc.

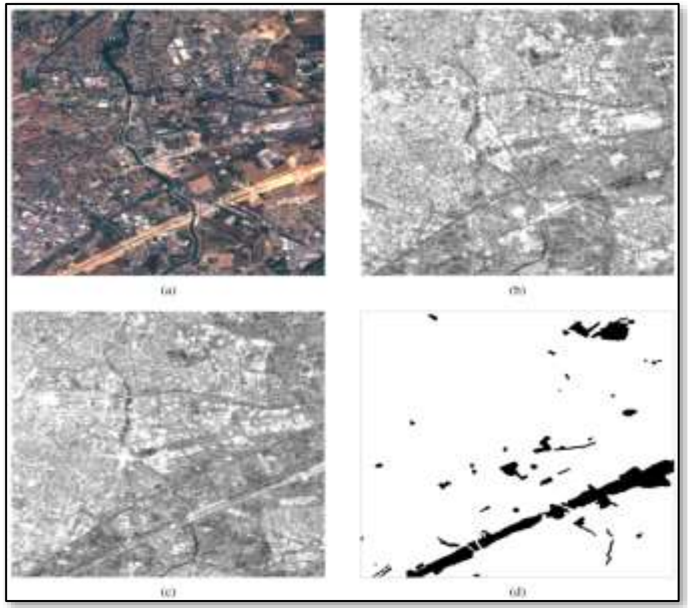
Before and After Satellite Images of the Earthquake-Affected Areas in Turkey

Background and Motivation

- **The current research mainly focus on post-doc analysis and has shown promising results by incorporating additional temporal and modal data, leading to significant performance improvements.**
- **Data availability, data preprocessing, and data labeling pose challenges for rapid response to earth's surface anomalies.**



Assessment of Building Damage Using Multi-Temporal Method

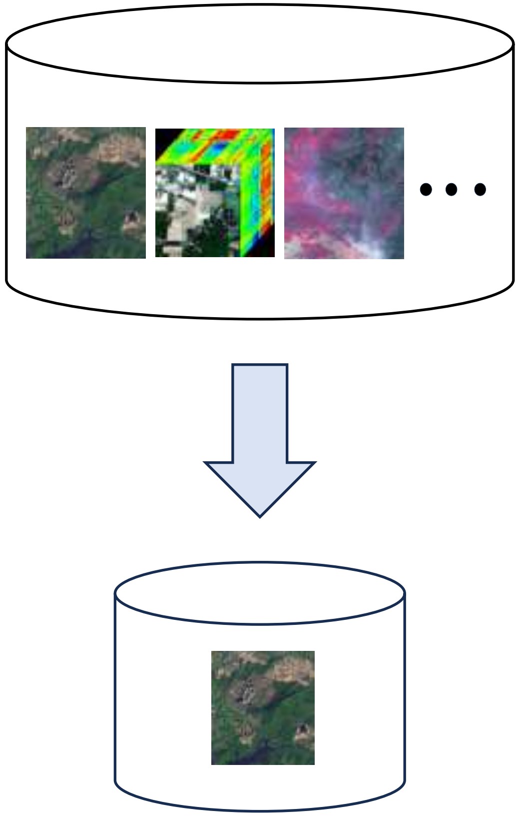


Extracting Disaster-Affected Areas Using Multi-Modal Method

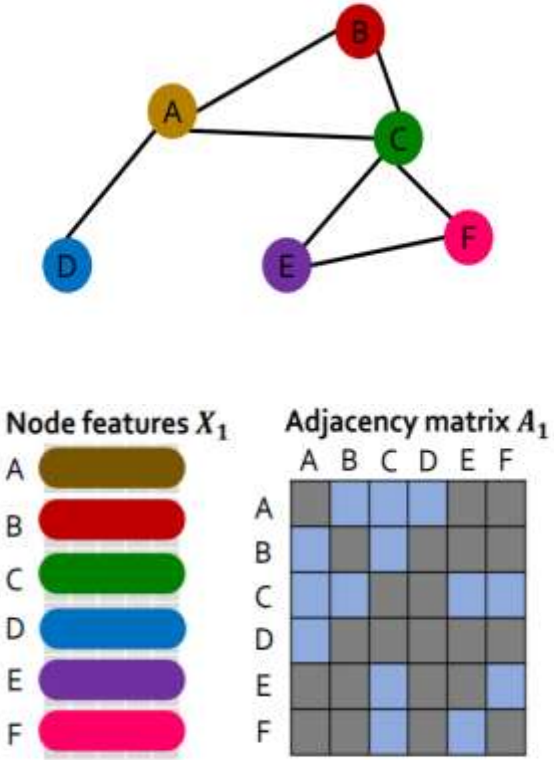
Weber, E., Kané, H. Building disaster damage assessment in satellite imagery with multi-temporal fusion. 2020.
Saha, S., Shahzad, M., Ebel, P., Zhu, X.X.: Supervised change detection using prechange optical-sar and postchange sar data. 2022

Background and Motivation

- **Reduce detection time and save valuable time for response.**



Simpler Data



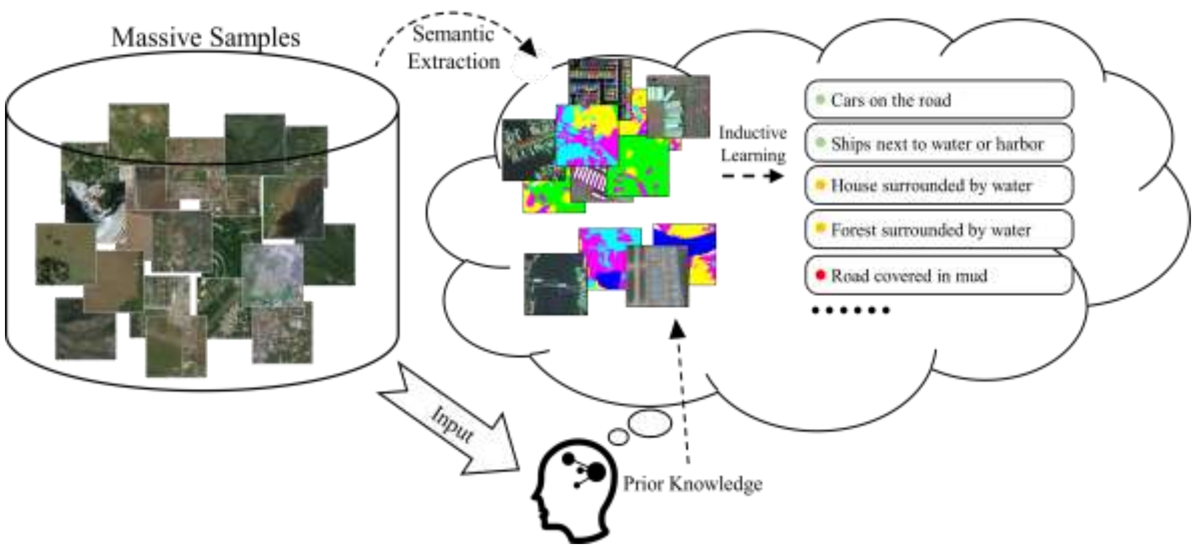
Lightweight and tailored model

Anomaly	Flood
	Landslide
	Debrisflow
	Hurricane
	Wildfire
	Earthquake
	Volcano
	Tornado
	Tsunami
	Fire
	Bushfire
Normal	

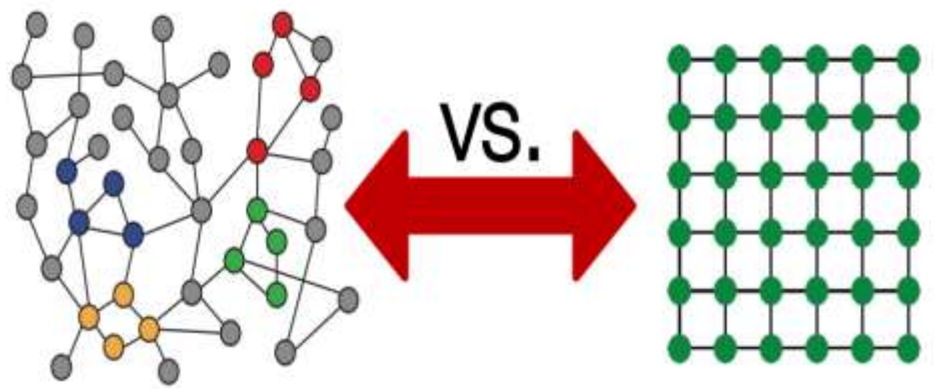
1 vs all

Background and Motivation

- We use graph neural networks as the core model, aiming to enable the model to explicitly capture semantic relationships between different geoentities and use them for inference.
- Irregular structure, Explicitly modeling relationships, Flexibility, etc.



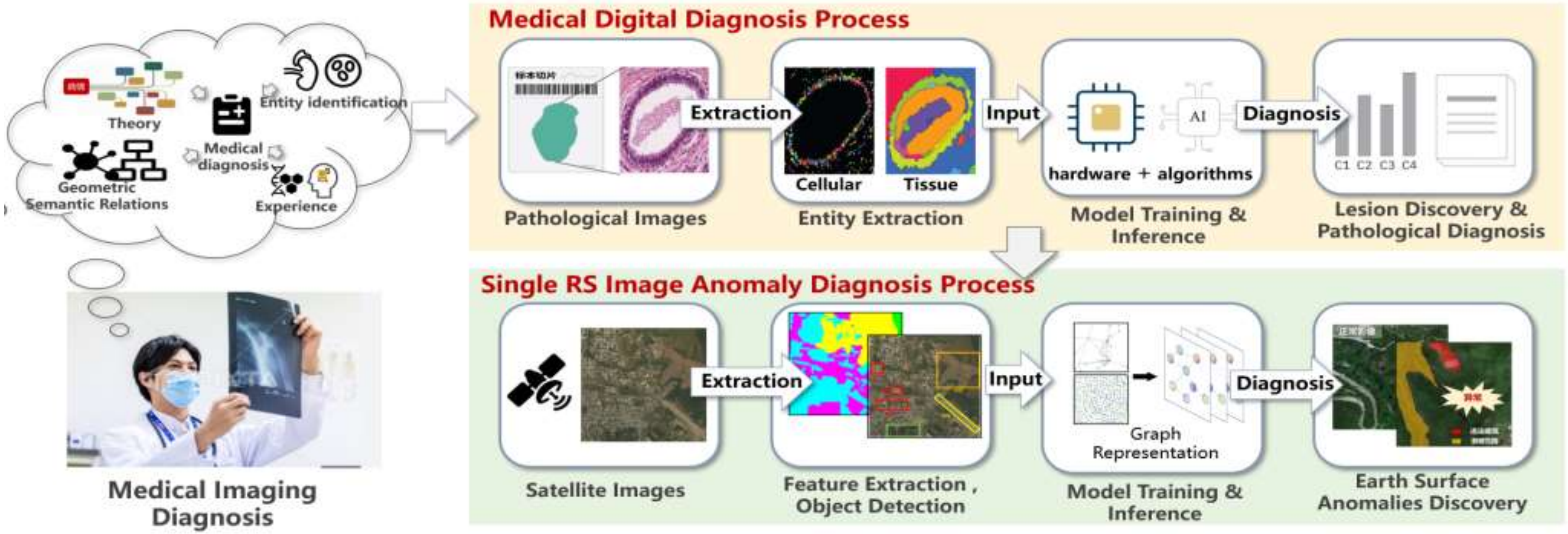
Simulated Process of Human Brain Interpret Satellite Images



Comparison of Graph and Regular Grid Image

Background and Motivation

- Inspired by the AI-based synergistic approach of doctors in diagnosing diseases at the cellular and tissue levels. We process satellite remote sensing images into graph structures at different levels, including geometric and semantic, facilitating earth surface anomaly detection.



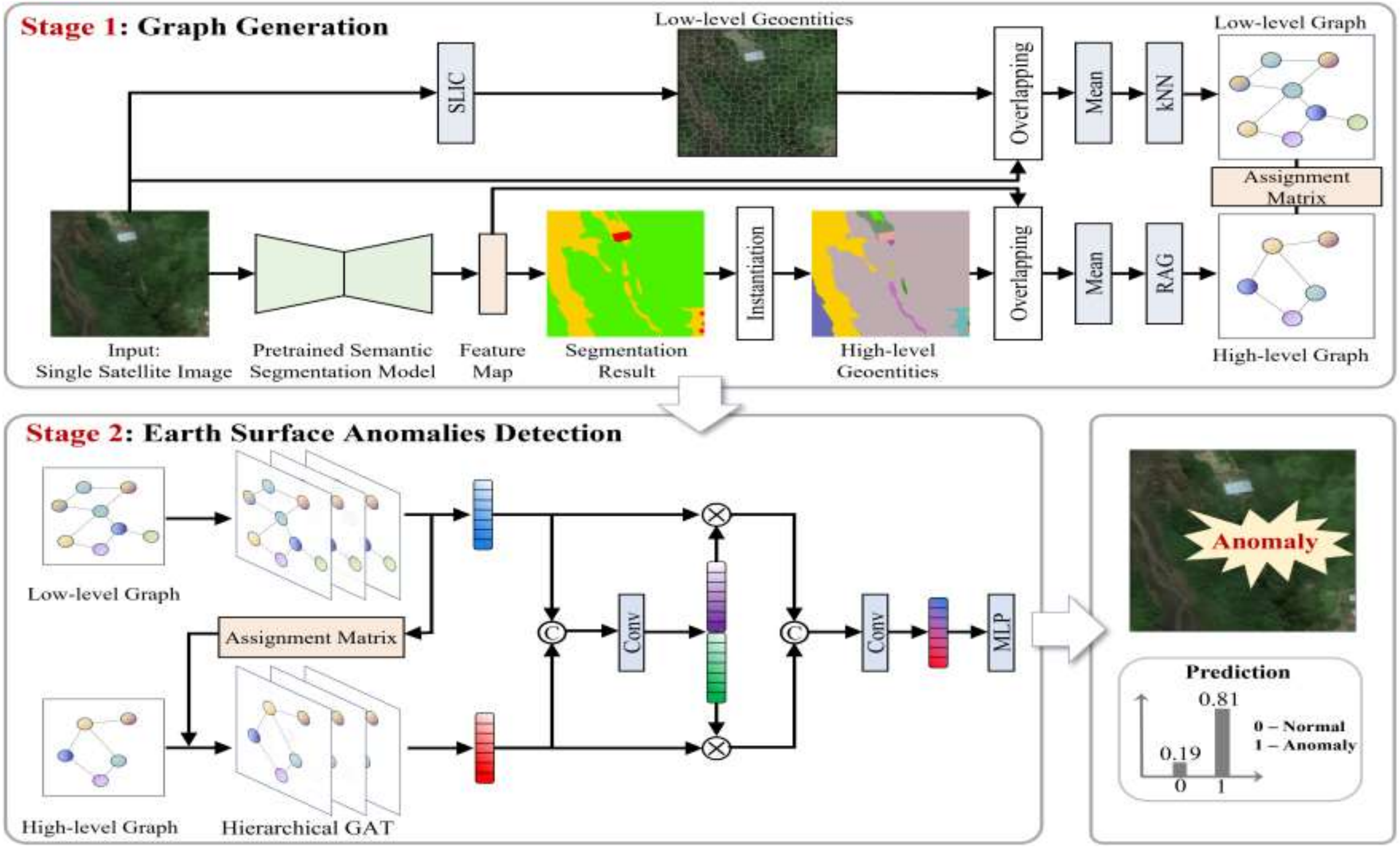
Simulating Doctor's Diagnostic Process for Earth’s Surface Anomaly Detection

Outline

- Background and Motivation
- **Method**
- Experiments
- Conclusion and Future Work

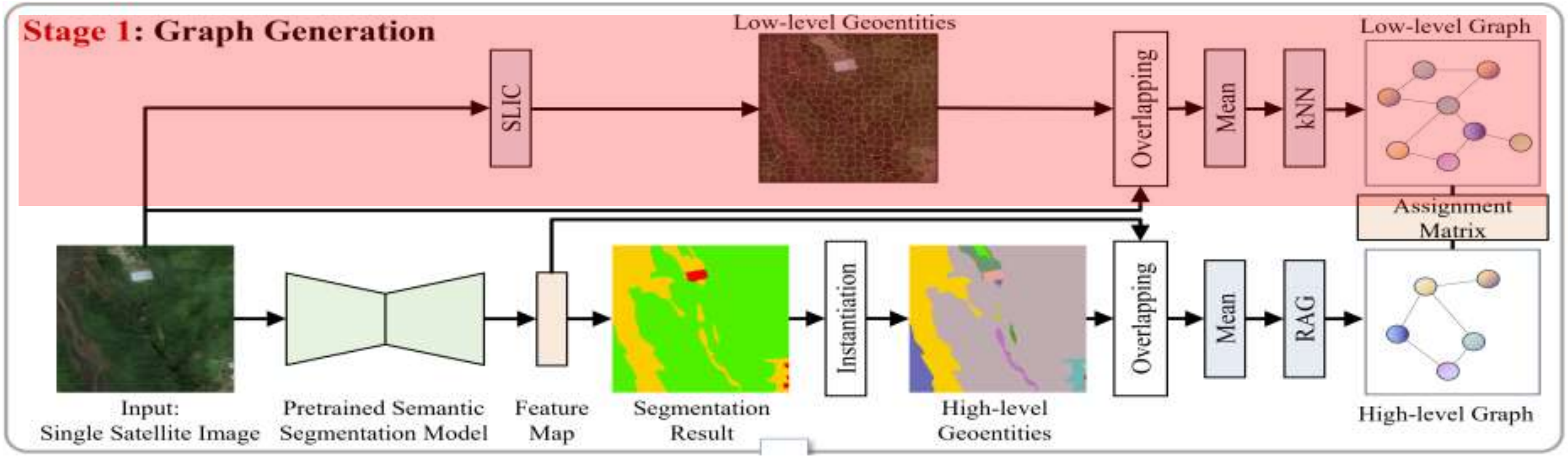
Method

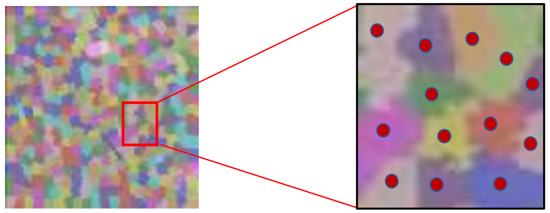
- **A hierarchical geometry-to-semantic fusion GNN framework**



Method

- **How to generate hierarchical graph?**



$f_{SLIC}($  $)=$ 

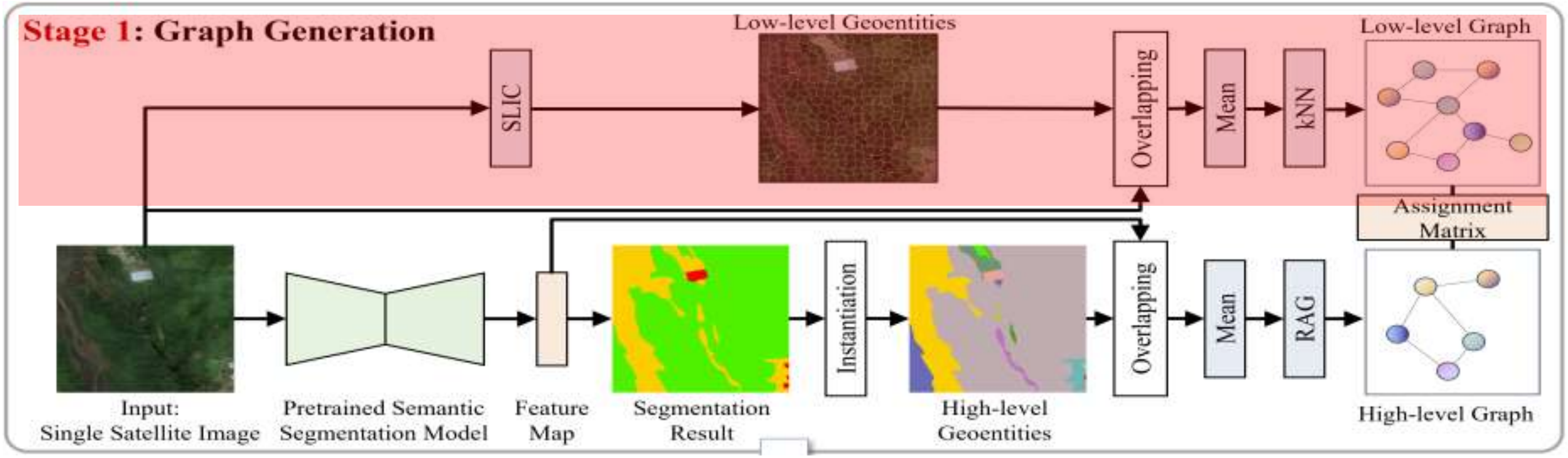
X $\quad$ S_1

$$N(v_i) = \frac{1}{m}\sum_{j=1}^{m}\begin{bmatrix} R_j \\ G_j \\ B_j \end{bmatrix},\ v_i \in V_{low}$$

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., Süsstrunk, S.: Slic superpixels compared to state-of-the-art superpixel methods. IEEE TPAMI. 2012.

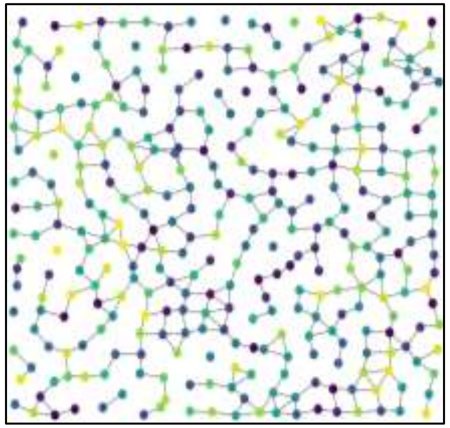
Method

- **How to generate hierarchical graph?**



k-Nearest Neighbors Algorithim:

$$u \in \{w | D(v,w) \leq d_k \wedge D(v,w) < \tau_{dist}, \forall w, v \in V_{low}\}$$

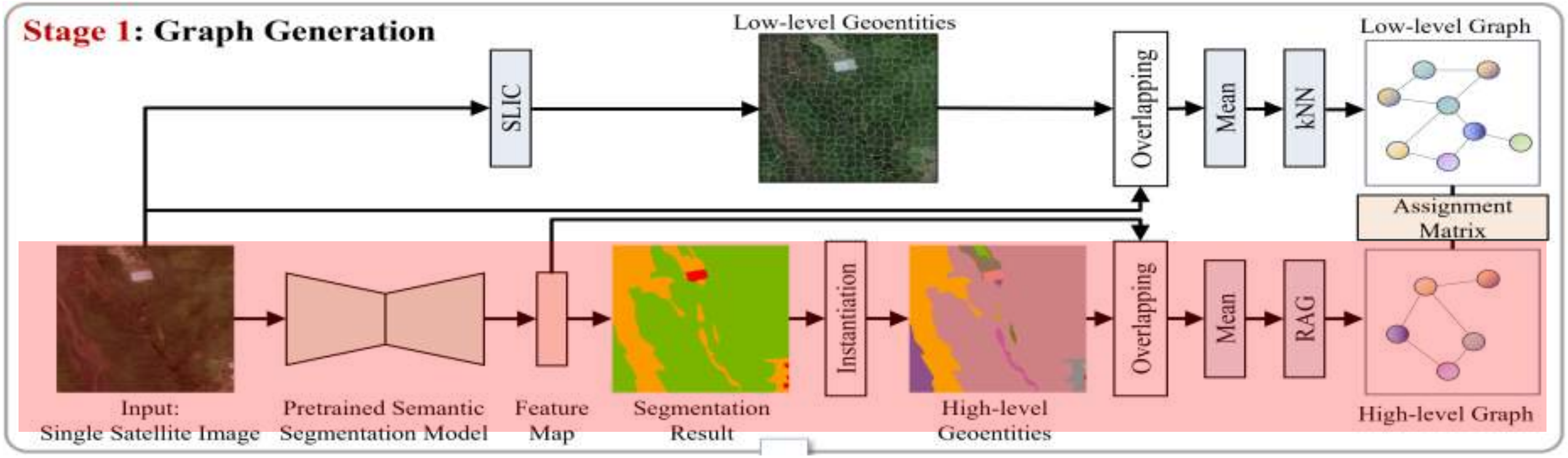


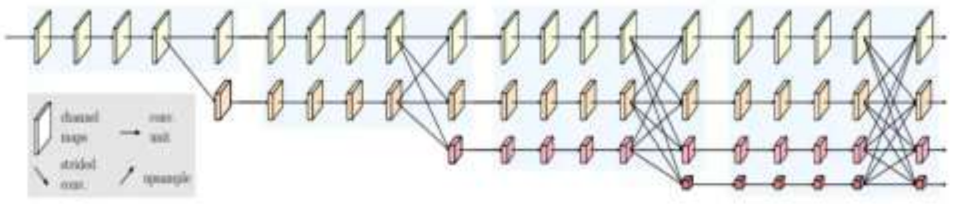
G_{low}

Fix, Evelyn, and Joseph Lawson Hodges. Discriminatory analysis. Nonparametric discrimination: Consistency properties. 1989.

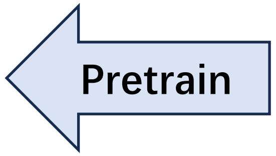
Method

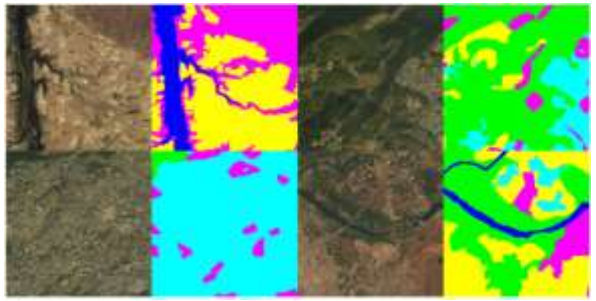
- **How to generate hierarchical graph?**





HRNet



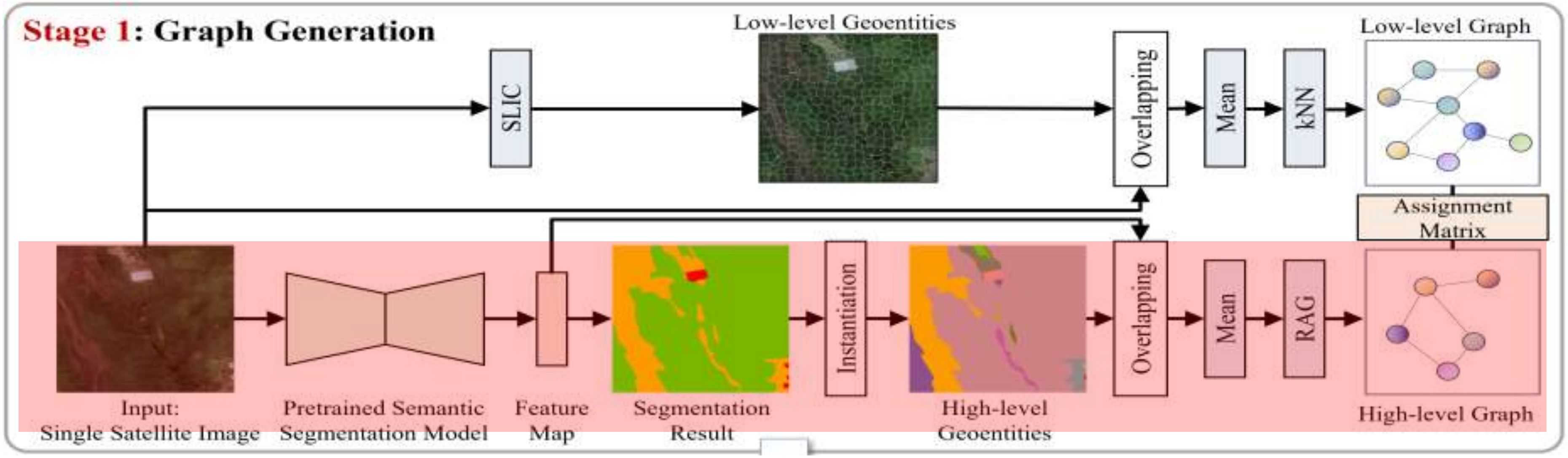


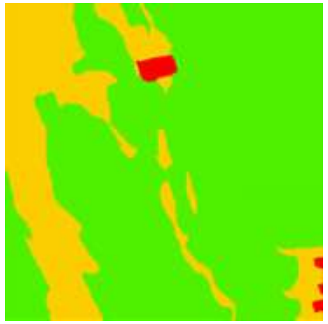
DeepGlobe Dataset

Wang, Jingdong, et al. Deep high-resolution representation learning for visual recognition. IEEE TPAMI. 2020.
Demir, Ilke, et al. Deepglobe 2018: A challenge to parse the earth through satellite images. CVPR Workshop. 2018.

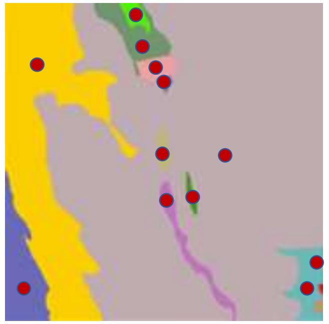
Method

- **How to generate hierarchical graph?**



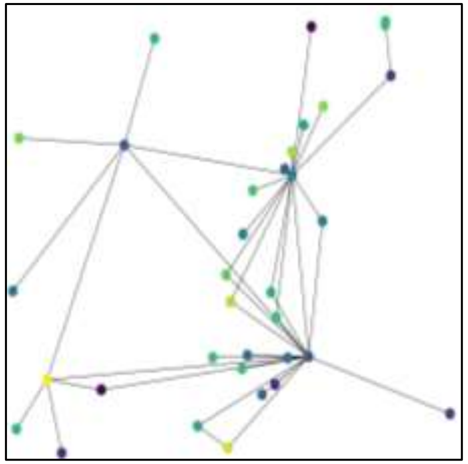


S_2



$\hat{S}_2$

RAG

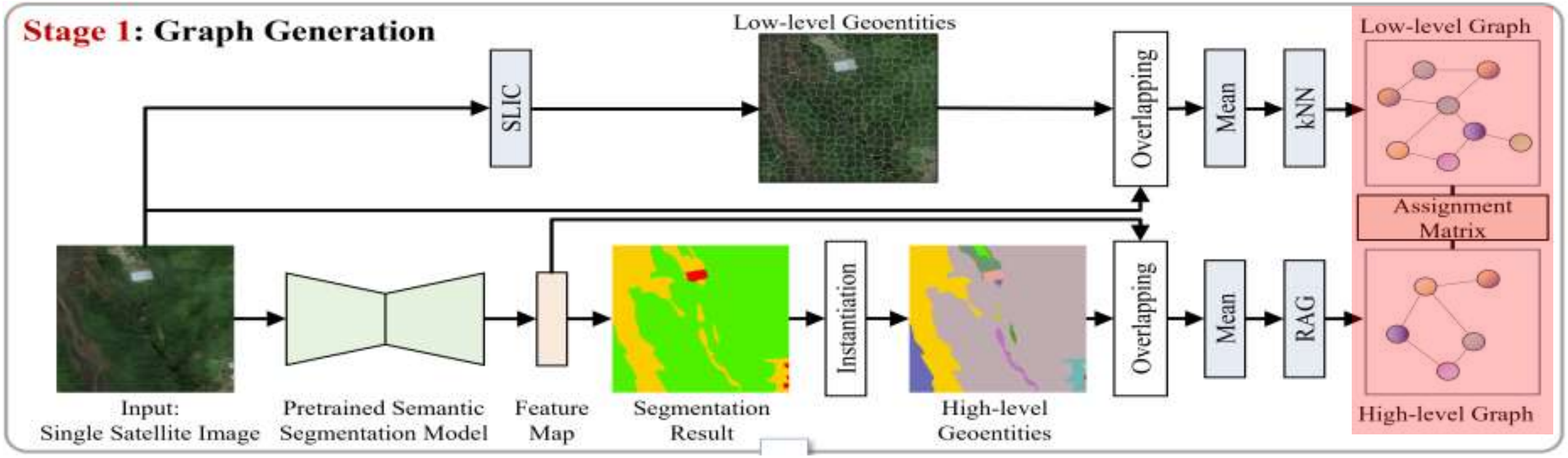


G_{high}

$$N(v_i) = \frac{1}{m}\sum_{j=1}^{m} F_s^j, \ v_i \in V_{high}$$

Method

- **How to generate hierarchical graph?**

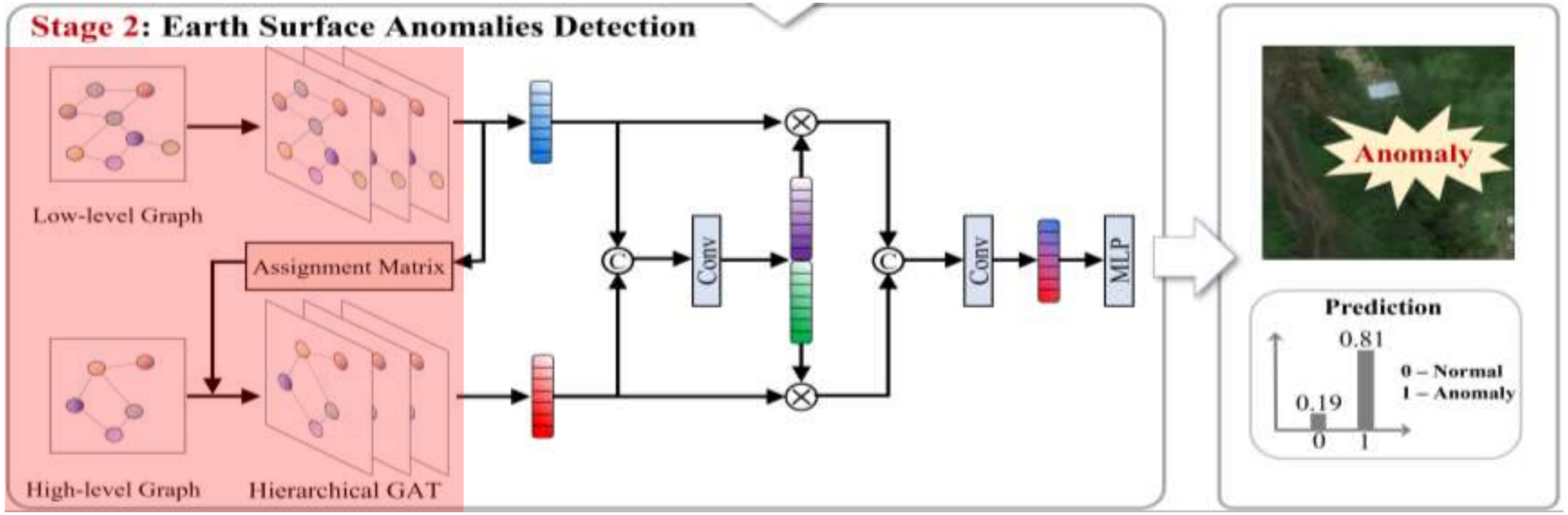


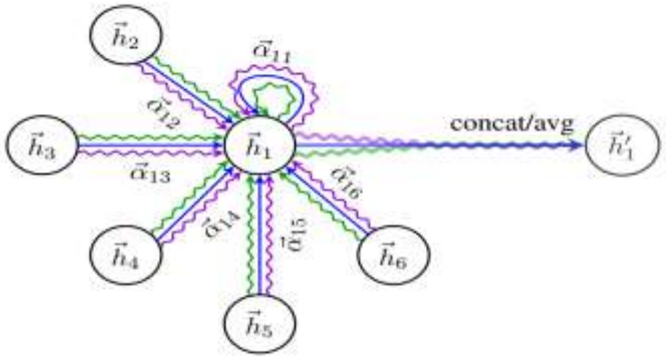
$$A_{low\to high}[i,j] = \begin{cases} 1 & \text{if} i^{\text{th}} \text{ low-level geoentity} \in j^{\text{th}} \text{ high-level geoentity} \\ 0 & \text{otherwise} \end{cases}$$

$$G_{joint} := \{G_{low}, G_{high}, A_{low\to high}\}$$

Method

- **How to learn from graph?**





$$h_i^{(l)} = \sigma\Big(\sum_{j\in N_i} \alpha_{ij}^{(l)} W^{(l)} h_j^{(l-1)} + b^{(l)}\Big),$$

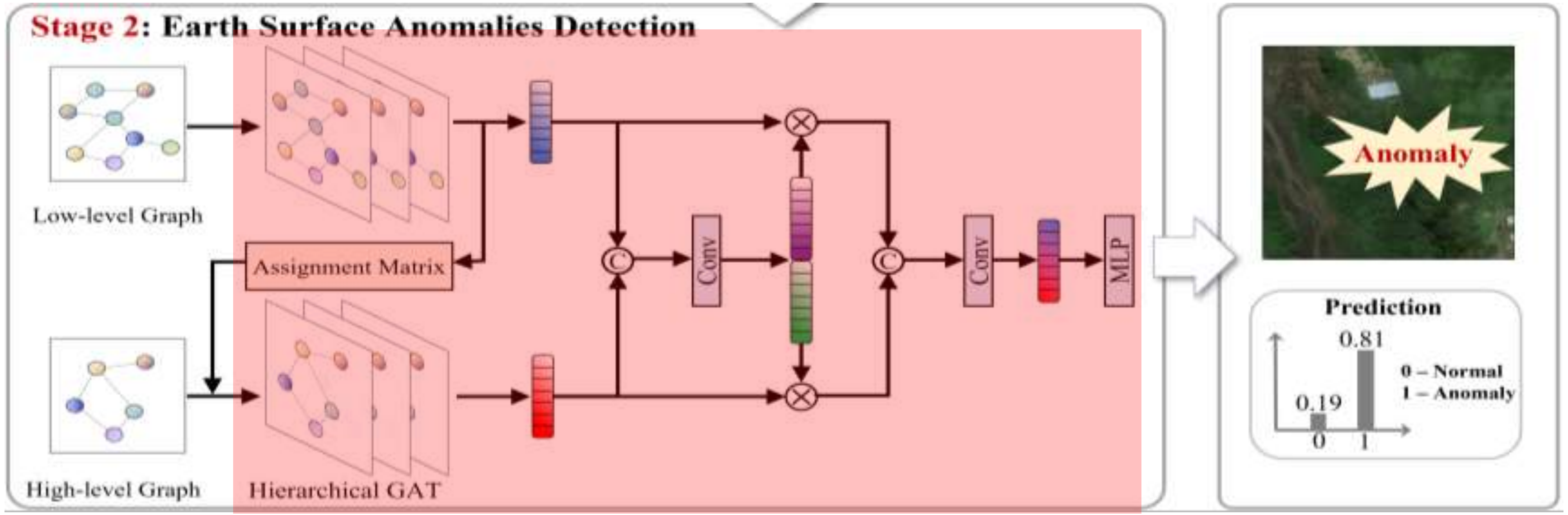
$$\alpha_{ij}^{(l)} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\boldsymbol{a}^{(l)^T}\left[W^{(l)}h_i^{(l-1)} \| W^{(l)}h_j^{(l-1)}\right]\right)\right)}{\sum_{k\in N_i}\exp\left(\mathrm{LeakyReLU}\left(\boldsymbol{a}^{(l)^T}\left[W^{(l)}h_i^{(l-1)} \| W^{(l)}h_k^{(l-1)}\right]\right)\right)}$$

Graph Attention Networks (GAT)

Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, Yoshua Bengio. Graph attention networks. 2017.

Method

- **How to learn from graph?**



$$h_{\text{high}}(w) = \left[H_{\text{high}}(w) || \sum_{v \in M(w)} \hat{h}_{low}(v) \right]$$

$$\mathbf{z} = f(\left[x_{low} \odot a_{low} || a_{high} \odot a_{high} \right])$$

$$[a_{low}, a_{high}] = [\sigma(f([x_{low}, x_{high}]), 1 - \sigma(f([x_{low}, x_{high}])]$$

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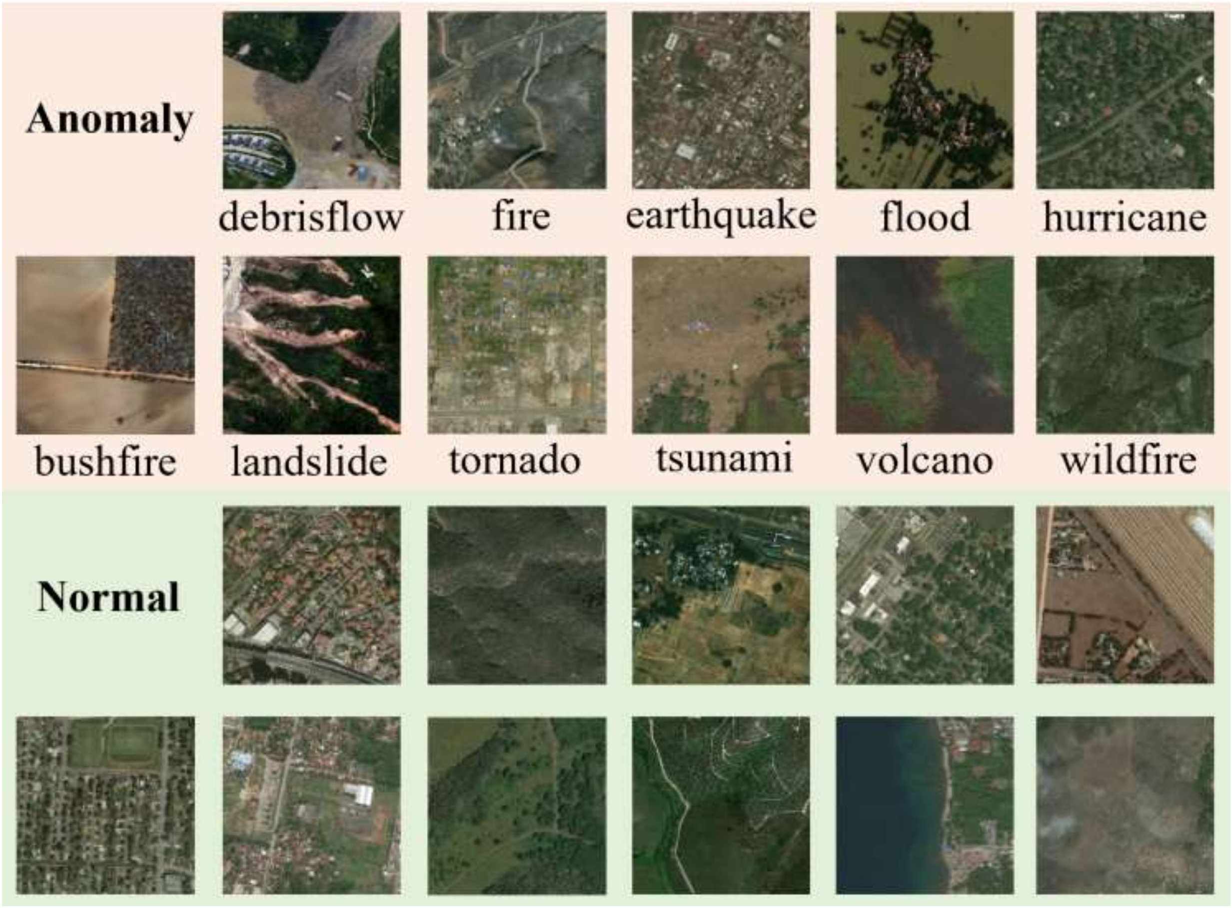
Experiments

- **ESAD (Earth Surface Anomaly Detection) Dataset**
- **13058 samples, 11 classes, high spatial resolution**

Class		Num
Anomaly	Flood	647
	Landslide	59
	Debrisflow	48
	Hurricane	1296
	Wildfire	1201
	Earthquake	14
	Volcano	217
	Tornado	254
	Tsunami	107
	Fire	1548
	Bushfire	996
Normal		6671

Statistics of ESAD Dataset



Examples of ESAD Dataset

Experiments

- **Comparison with baselines**

Quantitative result of comparison methods

Method	OA	Recall	AIT	Params
ResNet-50	91.05	90.42	16.63ms	25.61M
MobileNetV3	88.40	88.08	14.98ms	3.8M
ViT-B/32	93.71	93.40	16.67ms	88.21M
HGP-SL-Low	66.85	66.87	2.04ms	0.07M
HGP-SL-High	61.64	61.58	0.28ms	0.14M
HACT-Net	74.53	75.42	2.47ms	0.79M
Our method	83.89	83.86	6.04ms	1.01M

Experiments

- **Ablation Study**

Ablation Study of Proposed Method

Method	OA	Recall	AIT	Params
GAT-Low	65.15	66.80	2.88ms	0.09M
GAT-High	62.32	68.06	3.42ms	0.21M
Concat-GAT	78.41	77.25	6.92ms	1.02M
Our method	83.89	83.86	6.04ms	1.01M

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Conclusion and Future Work

- Better model performance
- Larger dataset
- Satellite in-orbit experiment

Thanks

cbachen1997@whu.edu.cn

gaozhinus@gmail.com