Structured Spectral Graph Learning for 3D Chest CT Volumes Multi-label Anomaly Classification

Theo Di Piazza   Carole Lazarus   Olivier Nempont   Loic Boussel

MICCAI 2025 Daejeon REPUBLIC OF KOREA
EMERGE 25

Motivations

Multi-label anomaly classification on 3D CT scans captures anomaly co-occurrence and provides a natural pretraining task for downstream applications.

Existing work

Local receptive fields of CNNs limit their ability to capture global contextual information across large 3D volumes.

Vision Transformers can be computationally expensive and often require extensive pre-training on large-scale datasets.

CT-Graph

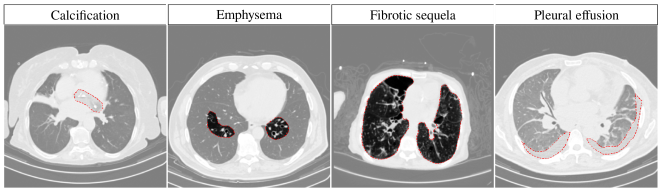
We formally define a 3D CT scan as a structured graph, where each node represents a triplet of axial slices.

Nodes features interact through a spectral domain convolution, before being aggregated and given to a classification head.

We evaluate the impact of graph topology, edge weighting strategy and graph convolutional operator.

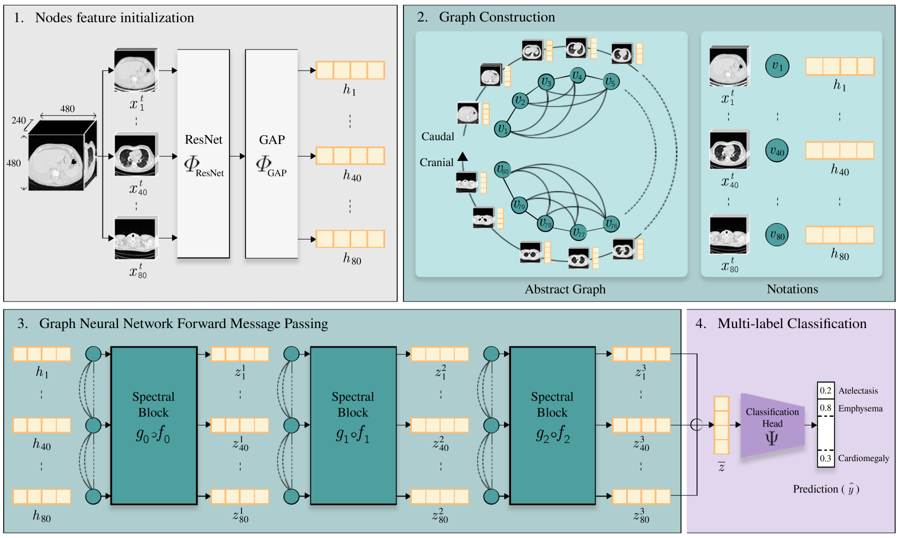
Dataset

- CT-RATE for train and evaluation
  ~21,000 unique patients
  18 abnormalities extracted from reports
  Non-contrasted 3D Chest Computed Tomography Volumes
- RAD-ChestCT for cross-dataset evaluation
  ~1,400 unique patients
  16 abnormalities shared with CT-RATE
  Non-contrasted 3D Chest Computed Tomography Volumes



Axial slices of 3D CT Scans with anomalies contoured in red, illustrating distinc visual characteristics.

Method



Nodes feature initialization

Axial slices of the 3D CT Scan are grouped by triplets. Each triplet is given to a 2D ResNet, followed by a Global Average Pooling layer.

Graph construction

Each triplet of axial slices represents a node. An undirected edge is defined between 2 nodes, if they are separated by at most q triplet slices.

$$\mathcal{E} = \{(v_i, v_j) \mid |i-j| \leq q\}$$

Edge weights are defined based on inter-slices distance.

$$w_{i,j} = 1 + \frac{1}{1+dist(i,j)} = 1 + \frac{1}{1+3\times|i-j|\times s_z}$$

Message passing

Nodes feature interact through Chebyshev convolutions, each followed by a FFN.

Classification

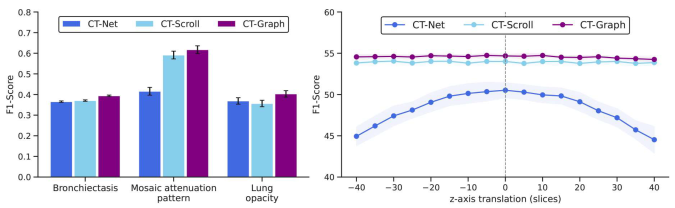
Nodes feature are averaged and given to a classification head to predict anomalies.

arXiv preprint

Quantitative results

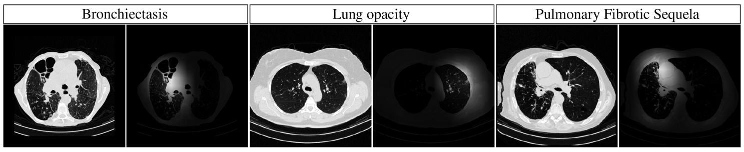
Dataset	Method	F1-Score	AUROC	Accuracy
CT-RATE	Random Pred.	27.78±0.51	49.88±0.62	49.89±0.31
	ViViT [2]	49.91±0.28	79.19±0.28	75.95±0.71
	Swin3D [24]	50.64±0.25	79.94±0.15	75.95±0.25
	CT-Net [13]	51.39±0.50	79.37±0.27	77.37±0.40
	CNN3D [1]	52.92±1.08	81.47±0.78	77.80±0.37
	CT-Scroll [11]	<u>53.97</u>±0.21	<u>81.80</u>±0.22	**79.49**±0.45
	CT-Graph	**54.59**±0.17	**82.44**±0.14	<u>78.66</u>±0.36
Rad-ChestCT	Random Pred.	35.91±0.41	49.68±0.55	50.40±0.32
	ViViT [2]	48.59±0.97	67.83±0.38	60.22±1.15
	Swin3D [24]	47.98±0.41	67.29±0.23	60.67±0.60
	CT-Net [13]	47.53±0.93	67.71±0.83	60.05±1.93
	CNN3D [1]	<u>49.28</u>±0.93	71.13±0.62	61.08±0.60
	CT-Scroll [11]	48.55±0.54	<u>71.21</u>±0.37	**63.02**±0.93
	CT-Graph	**49.52**±0.76	**72.18**±0.29	<u>62.60</u>±0.52

Quantitative results on the multi-label anomaly classification task. **Best** results, <u>second</u> best. Metrics are reported across 5 runs.



Anomalies with highest improvement in F1-Score over baselines (left) and robustness to patient body z-axis translation (right).

Qualitative results



GradCAM activation maps extracted from the 2D ResNet module.

Ablation study

Topology	Module	F1-Score	AUROC	Accuracy
Fully connected	Graph Attention	53.72±0.34	81.56±0.03	78.04±0.31
	Graph Conv.	53.73±0.36	81.99±0.40	78.15±0.31
	Spectral Conv.	<u>54.40</u>±0.15	<u>82.34</u>±0.12	<u>79.01</u>±0.55
Sparse	Graph Attention	54.06±0.19	82.22±0.05	78.59±0.25
	Graph Conv.	54.16±0.24	82.33±0.18	78.68±0.52
	Spectral Conv.	**54.41**±0.12	**82.47**±0.26	**79.12**±0.53

Impact of graph topology on different convolutional operators.

Discussion and acknowledgments

Future work may include 1) multi-view modeling with coronal and sagittal planes, and 2) an anatomy-driven graph construction.

We acknowledge the MICCAI Student Board, the program committee, and the anonymous EMERGE Workshop reviewers.

UNIVERSITÉ DE LYON
INSA INSTITUT NATIONAL DES SCIENCES APPLIQUÉES LYON
CREATIS
HCL HOSPICES CIVILS DE LYON
PHILIPS