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# **FACT: Fuzzy Alignment with Comorbidity Topology for Reliable Multi-Label Medical Image Diagnosis**

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# Background



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## Single-label Classification



Natural images often contain one primary object  
The task is to assign a single label (e.g., "cat")

direct extension

suboptimal

## Multi-label Diagnosis (MLD)



Medical images often present **multiple co-occurring conditions** simultaneously, which are inherently more complex

Chest X-ray (e.g., Pneumonia, Effusion, Cardiomegaly).

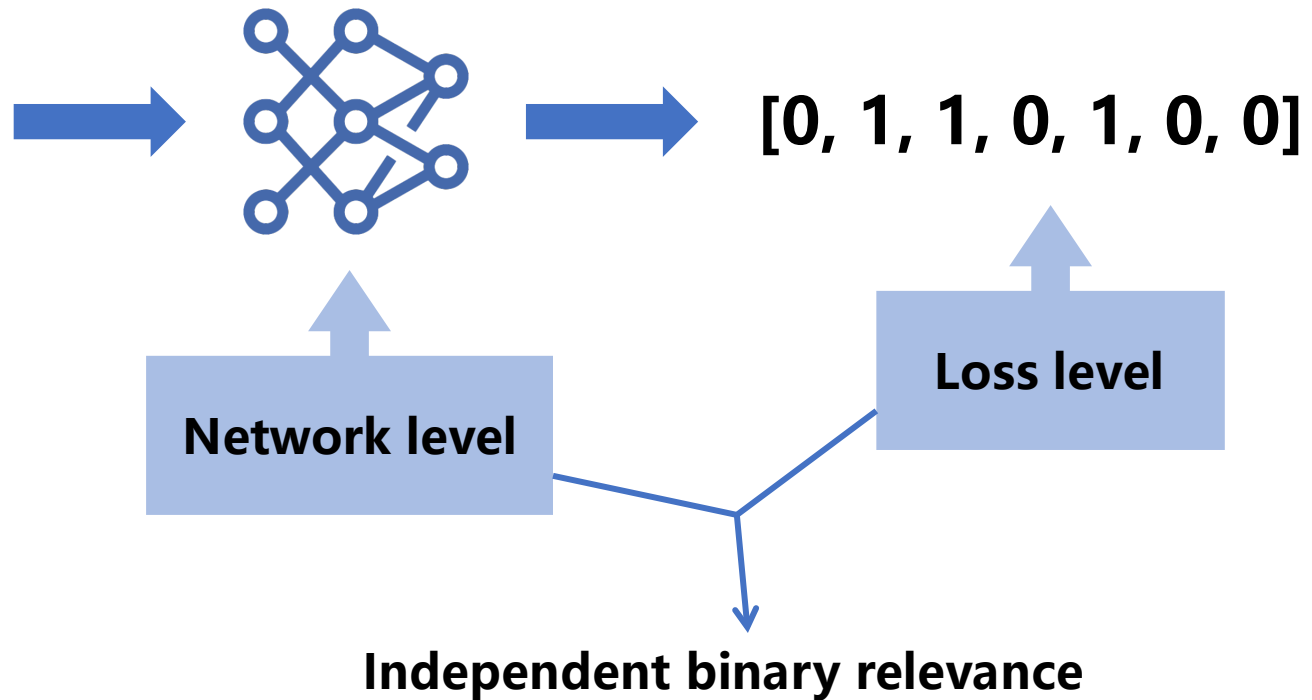
# Background



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## Current Work

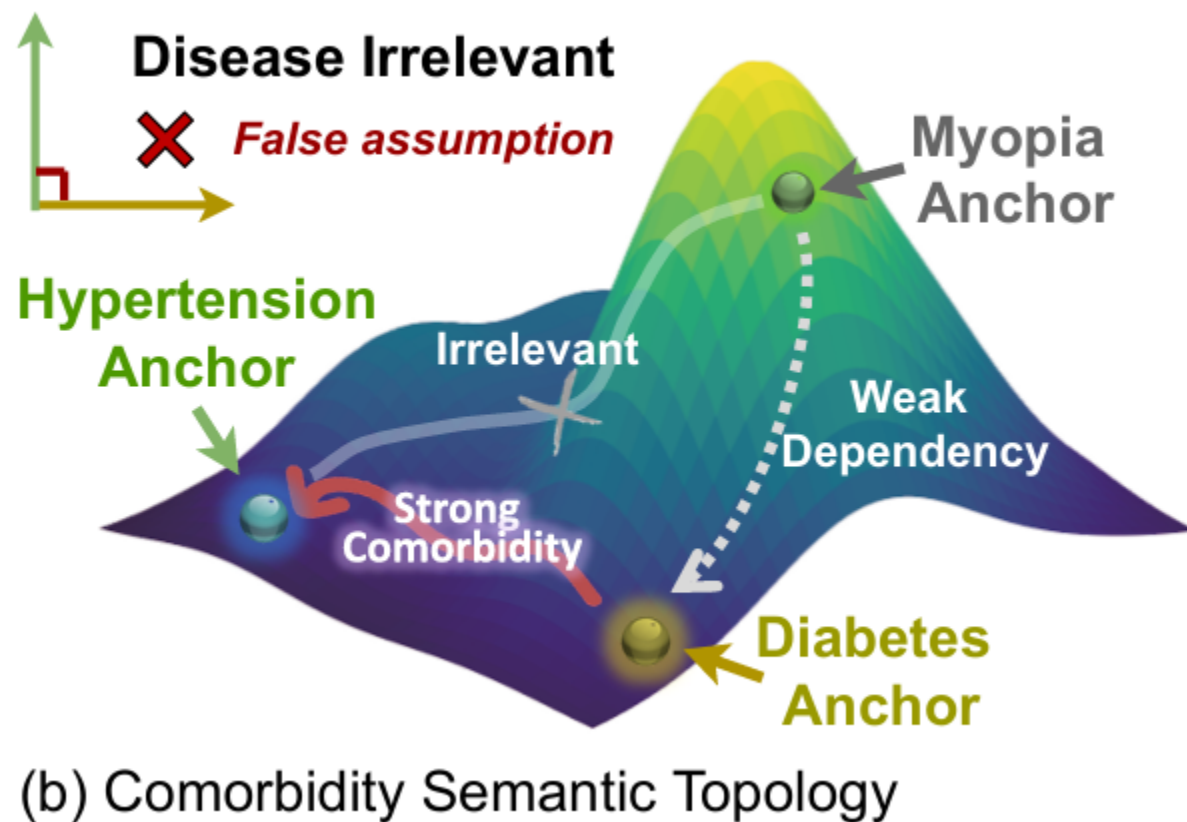
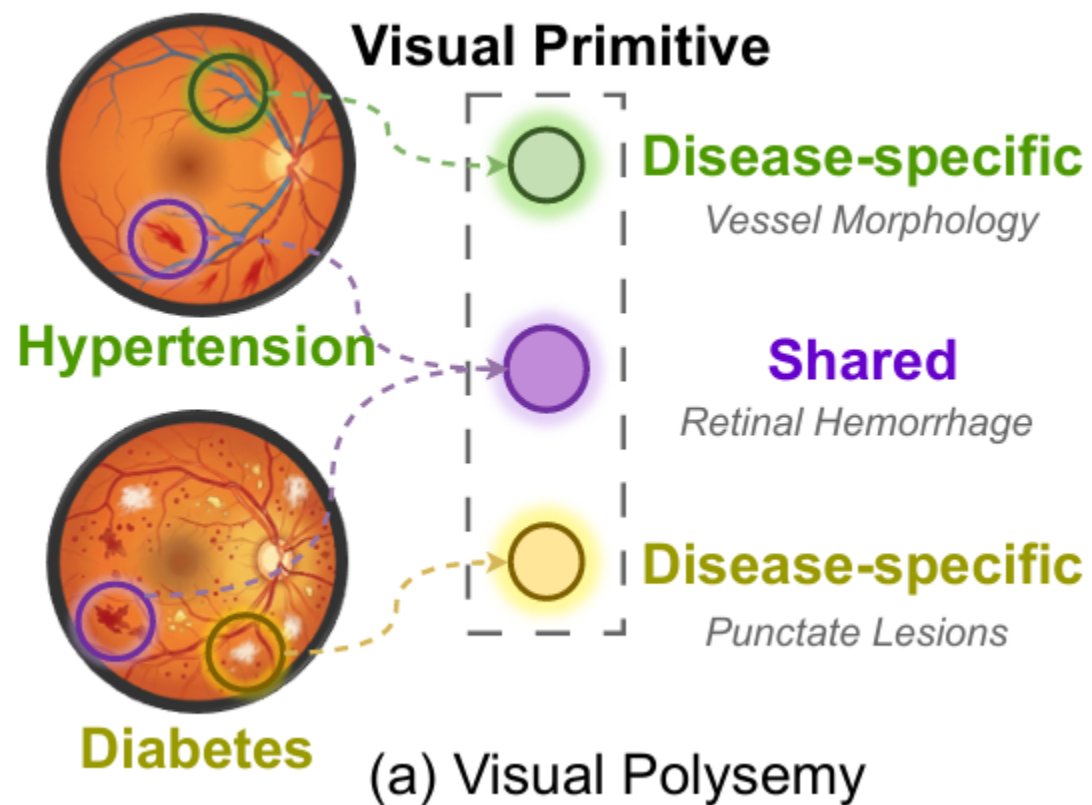


# Motivation



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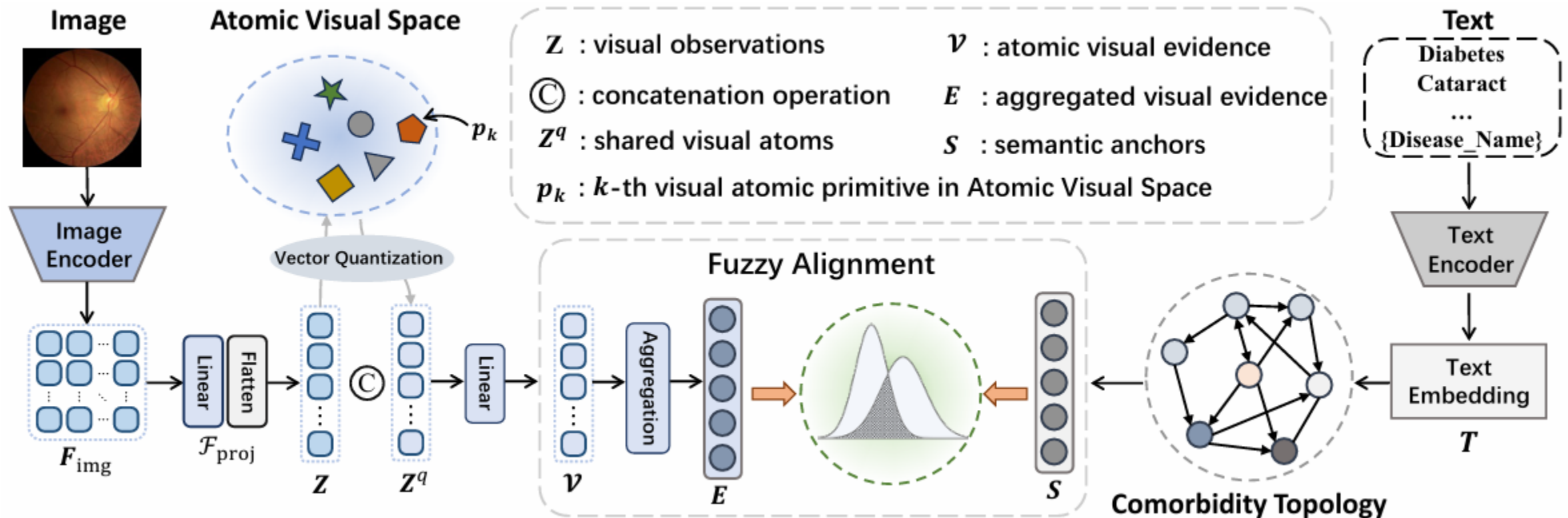
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# Methodology



- (3) Fuzzy Alignment {
- (1) Atomic Visual Space → captures visual polysemy
  - (2) Comorbidity Topology → encodes disease relationship



## (1) Atomic Visual Space

$$\mathbf{Z} = \mathcal{F}_{\text{proj}}(\mathbf{F}_{\text{img}}) \in \mathbb{R}^{M \times d} \quad M = H \times W$$

### Vector Quantization (VQ)

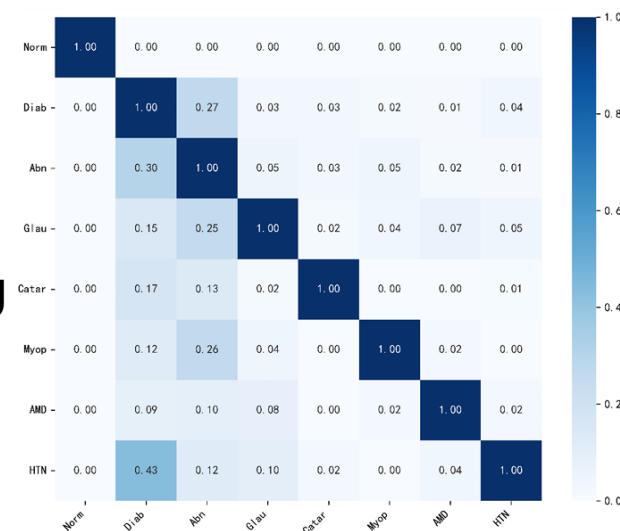
$$z_m^q = p_k, \quad \text{where } k = \arg \min_{j \in \{1, \dots, K\}} \|z_m - p_j\|_2.$$

## (2) Comorbidity Topology

$$\text{GCN} \quad \mathbf{S}^{(l+1)} = \text{RELU} \left( \tilde{\mathbf{D}}^{-\frac{1}{2}} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-\frac{1}{2}} \mathbf{S}^{(l)} \mathbf{W}^{(l)} \right).$$

① Adjacency matrix  $\mathbf{A}$  ← correlation matrix

② Node features  $\mathbf{S}^0$  ← disease text embedding



## (3) Fuzzy Alignment

**Visual feature (VQ)**  $\mathcal{V} \in \mathbb{R}^{M \times d}$

**Semantic anchor (GCN)**  $\mathcal{S} \in \mathbb{R}^{C \times d}$

**Semantic interface operator**  $E = \mathcal{I}(\mathcal{V}) = Q + \text{Sigmoid}\left(\frac{Q\mathcal{V}^\top}{\sqrt{d}}\right) \mathcal{V}$

**Fuzzy membership**  $\mu_c = \exp\left(-\frac{\|e_c - s_c\|^2}{\tau}\right)$

Derived from continuity & semantic consistency (see appendix A.1)

## Fuzzy loss

$$\mathcal{L}_{\text{fuzzy}} = \mathcal{L}_{\text{point}}(\boldsymbol{\mu}, \mathbf{y}) + \alpha \cdot \mathcal{L}_{\text{set}}(\boldsymbol{\mu}, \mathbf{y}). \quad (\text{see appendix A.3})$$

**Point loss**

**Set loss**

$$\mathcal{L}_{\text{point}} = \log\left(1 + \sum_{c:y_c=0} r_c\right) + \log\left(1 + \sum_{c:y_c=1} r_c\right)$$

$$\mathcal{L}_{\text{set}} = 1 - \mathcal{J}(\boldsymbol{\mu}, \mathbf{y})$$

## Total loss

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{fuzzy}} + \gamma \cdot \mathcal{L}_{\text{commit}}$$

$$\mathcal{L}_{\text{commit}} = \|\text{sg}[\mathbf{Z}] - \mathbf{Z}^q\|_2^2 + \beta \|\mathbf{Z} - \text{sg}[\mathbf{Z}^q]\|_2^2$$

# Experiment



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Dataset	Modal	Data Scale	Num of Classes	Other Description
<b>ODIR-5K</b>	<b>Color Fundus image</b>	<b>5000 (tiny)</b>	<b>8</b>	<b>N/A</b>
<b>NIH-Chest</b>	<b>X-ray</b>	<b>112,120 (medium)</b>	<b>14</b>	<b>Long-tailed</b>
<b>RSNA-IHD</b>	<b>CT</b>	<b>752,802 (large)</b>	<b>5</b>	<b>Long-tailed</b>
<b>CXR-LT</b>	<b>X-ray</b>	<b>377,110 (large)</b>	<b>40</b>	<b>Extremely Long-tailed &amp; Noisy</b>

# Experiment



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Methods	Type	Ref.	Backbone	Param (M)	Flops (G)
TransferNet (2021)	Network- centric	BSPC'21	ResNet50	23.52	4.13
ASL (2021)	Objective-centric	CVPR'21	ResNet50	23.52	4.13
RAL (2023)	Objective-centric	ICCV'23	ResNet50	23.52	4.13
TADCL (2023)	Network- centric	MIA'23	ViT	61.36	8.84
Two-Way (2023)	Objective-centric	CVPR'23	ResNet50	23.52	4.13
CTransCNN (2023)	Network- centric	KBS'23	CNN+ViT	33.99	10.57
LDR (2024)	Network- centric	ACMMM'24	ResNet50	25.51	8.42
SupCon (2024)	Objective-centric	AAAI'24	ResNet50	23.52	4.13
MultiCo (2025)	Objective-centric	arxiv'25	ResNet50	23.52	4.13
HydraViT (2025)	Network- centric	BSPC'25	ResNet50	39.22	16.58
FACT (Ours)	–	–	ResNet50	25.87	4.21

# Experiment



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Methods	ODIR-5K				NIH-Chest				RSNA-IHD			
	mAP $\uparrow$	F1 $\uparrow$	AUC $\uparrow$	Avg. $\uparrow$	mAP $\uparrow$	F1 $\uparrow$	AUC $\uparrow$	Avg. $\uparrow$	mAP $\uparrow$	F1 $\uparrow$	AUC $\uparrow$	Avg. $\uparrow$
TransferNet (2021)	64.30	86.29	89.01	79.87	51.71	90.12	86.73	76.19	84.53	90.36	95.44	90.11
ASL (2021)	59.69	87.84	90.41	79.31	42.32	86.31	85.41	71.35	83.07	91.97	96.15	90.40
RAL (2023)	59.61	86.86	89.77	78.75	38.63	83.51	83.78	68.64	82.91	92.02	96.24	90.39
TADCL (2023)	65.04	86.57	86.45	79.35	41.05	86.91	84.22	70.73	<u>87.47</u>	92.07	96.32	<u>91.95</u>
Two-Way (2023)	55.93	84.13	91.17	77.08	46.38	84.81	86.70	72.63	57.51	79.17	94.37	77.02
CTransCNN (2023)	69.30	<u>90.29</u>	91.35	<u>83.65</u>	52.40	87.88	85.61	75.30	85.99	90.45	94.69	90.38
LDR (2024)	<u>69.69</u>	89.79	90.81	83.43	57.81	90.01	<u>87.52</u>	<u>78.45</u>	84.85	89.41	94.54	89.60
SupCon (2024)	67.43	86.75	90.62	81.60	<u>58.82</u>	89.28	86.08	78.06	84.59	90.03	95.12	89.91
MultiCo (2025)	68.30	89.14	<u>91.45</u>	82.96	54.32	90.14	87.04	77.17	86.70	<u>92.11</u>	96.22	91.68
HydraViT (2025)	67.92	88.25	90.22	82.13	54.60	<u>90.33</u>	86.96	77.30	86.39	91.22	<u>96.33</u>	91.31
FACT (Ours)	<b>72.61</b>	<b>90.91</b>	<b>92.97</b>	<b>85.50</b>	<b>58.95</b>	<b>90.44</b>	<b>87.81</b>	<b>79.07</b>	<b>89.72</b>	<b>92.97</b>	<b>96.90</b>	<b>93.20</b>
$\Delta$	+2.92	+0.62	+1.52	+1.85	+0.13	+0.11	+0.29	+0.62	+2.25	+0.86	+0.57	+1.25

“ $\Delta$ ” represents the difference in metrics between our method and the second-best method.

# Experiment



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(see Tab. 14)

Diseases	Prevalence	Group	Methods				
			MultiCo(2025)	LDR(2024)	HydraViT(2025)	Ours	$\Delta$
Adenopathy	1.19%	Middle	68.50	70.69	76.28	<b>78.55</b>	+2.27
Atelectasis	28.26%	Head	79.42	80.05	<u>80.11</u>	<b>80.19</b>	+0.08
Azygos Lobe	0.06%	Tail	69.77	<u>73.28</u>	69.72	<b>85.39</b>	+12.11
Calcification of the Aorta	1.46%	Middle	76.90	<u>85.88</u>	81.74	<b>87.95</b>	+2.07
Cardiomegaly	30.38%	Head	79.04	79.45	<b>79.52</b>	<u>78.58</u>	-0.94
Clavicle Fracture	0.06%	Tail	58.55	62.96	64.67	<b>76.23</b>	11.56
Consolidation	6.82%	Middle	74.90	<u>76.62</u>	<b>76.98</b>	76.60	-0.38
Edema	17.18%	Head	82.82	83.39	<b>84.15</b>	<u>83.40</u>	-0.75
Emphysema	1.36%	Middle	82.00	86.98	<b>88.60</b>	<u>88.19</u>	0.41
Enlarged Cardiomediastinum	11.18%	Head	55.34	55.49	<b>59.45</b>	<u>58.61</u>	-0.84
Fibrosis	0.41%	Tail	76.40	85.06	87.89	<b>89.21</b>	+1.32
Fissure	1.00%	Middle	59.03	67.64	<u>68.02</u>	<b>76.63</b>	+8.61
Fracture	4.34%	Middle	64.02	68.41	<u>70.50</u>	<b>74.05</b>	+3.55
Granuloma	0.97%	Tail	70.36	73.46	<u>73.82</u>	<b>76.16</b>	+2.34
Hernia	1.40%	Middle	74.88	<b>85.77</b>	84.76	<u>85.57</u>	-0.20
Hydropneumothorax	0.26%	Tail	74.78	90.67	<u>93.14</u>	<b>93.82</b>	+0.68
Infarction	0.29%	Tail	49.14	51.67	<u>56.27</u>	<b>61.04</b>	+4.77
Infiltration	3.72%	Middle	54.65	56.80	<u>57.71</u>	<b>58.10</b>	+0.39
Kyphosis	0.20%	Tail	78.13	<u>87.99</u>	86.07	<b>90.19</b>	+2.20
Lobar Atelectasis	0.06%	Tail	48.99	<u>82.26</u>	78.35	<b>85.03</b>	+2.77
Lung Lesion	0.92%	Tail	65.33	69.70	<u>73.82</u>	<b>76.36</b>	+2.54
Lung Opacity	31.69%	Head	74.07	74.83	<u>75.64</u>	<b>75.77</b>	+0.13
Mass	2.03%	Middle	70.21	73.62	<u>75.34</u>	<b>77.45</b>	+2.21
Nodule	2.63%	Middle	69.90	72.41	<u>72.91</u>	<b>74.91</b>	+2.00
Normal	12.28%	Head	79.27	78.98	<b>79.58</b>	<u>79.42</u>	-0.16
Pleural Effusion	29.27%	Head	89.42	89.89	<b>90.42</b>	<u>89.92</u>	-0.50
Pleural Other	0.20%	Tail	64.56	81.37	<u>82.13</u>	<b>83.49</b>	+1.36
Pleural Thickening	1.12%	Middle	71.28	77.81	<u>79.55</u>	<b>83.25</b>	+0.70
Pneumomediastinum	0.31%	Tail	56.93	73.61	<u>80.06</u>	<b>83.41</b>	+3.35
Pneumonia	16.84%	Head	60.35	61.92	<b>62.68</b>	<u>62.49</u>	-0.19
Pneumoperitoneum	0.24%	Tail	61.81	71.14	<u>74.33</u>	<b>79.91</b>	+5.58
Pneumothorax	6.31%	Middle	78.86	80.56	<u>82.67</u>	<b>82.70</b>	+0.03
Pulmonary Embolism	0.66%	Tail	49.56	51.52	<u>58.94</u>	<b>59.37</b>	+0.43
Pulmonary Hypertension	0.35%	Tail	58.81	75.02	<u>76.71</u>	<b>77.94</b>	+1.23
Rib Fracture	3.29%	Middle	62.23	67.68	<u>70.88</u>	<b>74.14</b>	+3.26
Round(ed) Atelectasis	0.05%	Tail	57.21	<u>92.11</u>	<b>92.59</b>	90.18	-2.41
Subcutaneous Emphysema	0.97%	Tail	90.49	94.16	<u>95.59</u>	<b>96.08</b>	+0.49
Support Devices	41.42%	Head	91.79	91.75	<u>91.85</u>	<b>92.53</b>	+0.68
Tortuous Aorta	1.11%	Middle	73.47	75.63	<u>78.35</u>	<b>79.68</b>	+1.33
Tuberculosis	0.72%	Tail	69.28	71.47	<u>76.03</u>	<b>76.60</b>	+0.57

" $\Delta$ " represents the difference in metrics between our method and the second-best method.

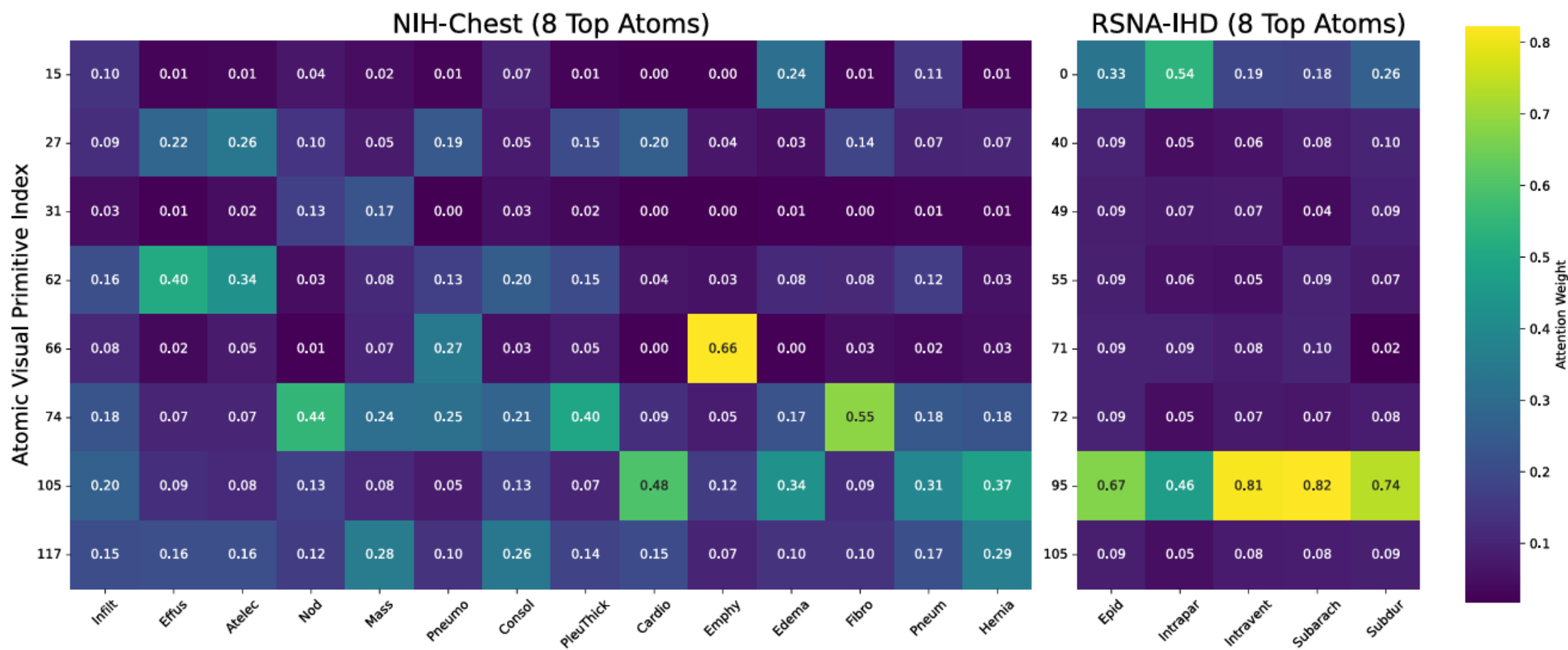
# Experiment



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## Effectiveness of polysemy modeling using Atomic Visual Space



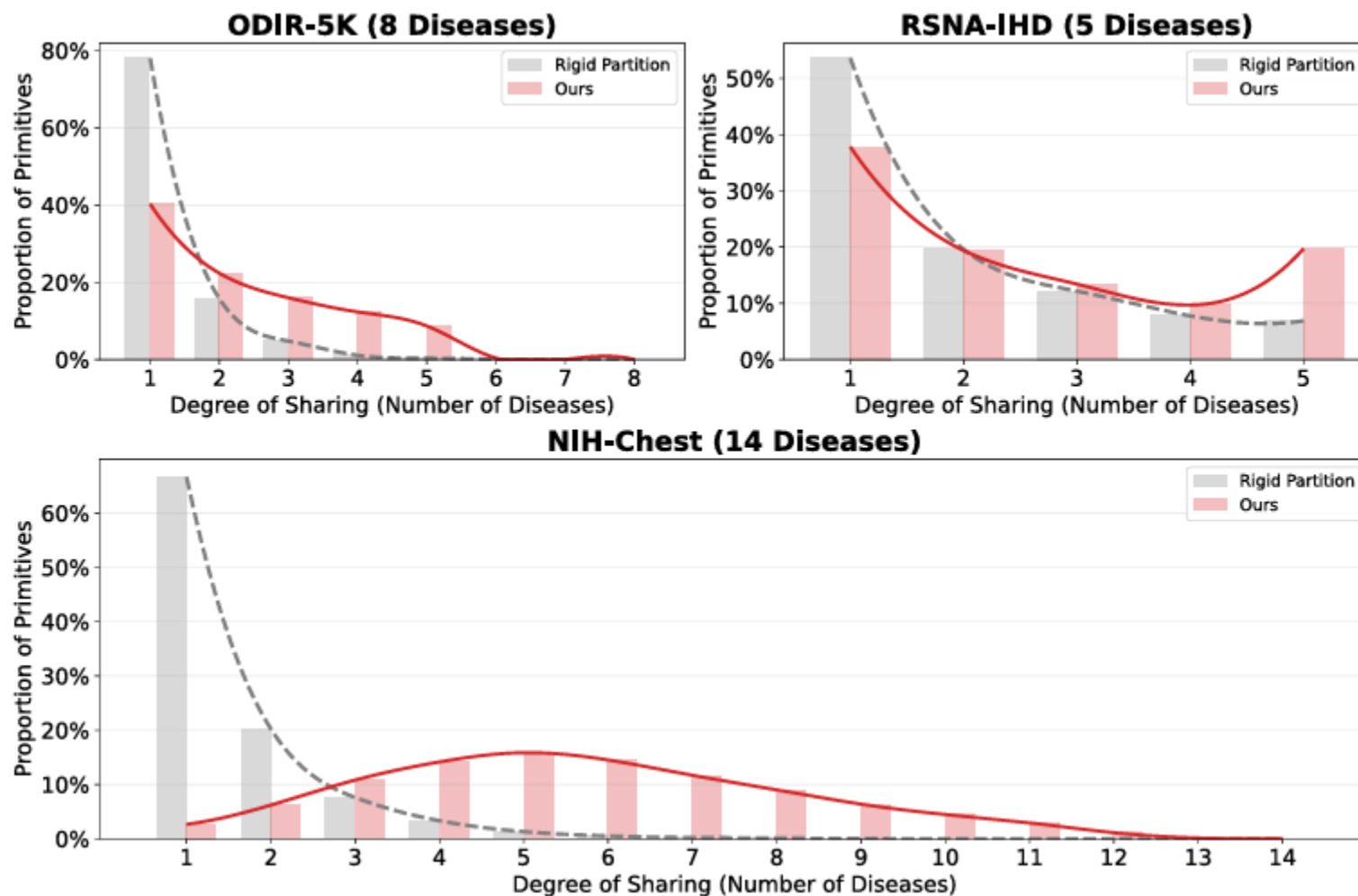
# Experiment



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## Effectiveness of polysemy modeling using Atomic Visual Space



## Effectiveness of Fuzzy membership using Gaussian kernel

Kernels	ODIR-5K				NIH-Chest				RSNA-IHD			
	mAP↑	F1↑	AUC↑	Avg.↑	mAP↑	F1↑	AUC↑	Avg.↑	mAP↑	F1↑	AUC↑	Avg.↑
Linear	69.94	89.64	91.82	83.80	51.94	89.85	87.23	76.34	89.15	92.16	96.64	92.65
Cosine	68.93	89.66	91.66	83.42	52.69	90.15	87.45	76.76	89.14	92.03	96.65	92.61
Laplacian	30.98	85.36	76.20	64.18	27.63	88.70	76.04	64.12	48.66	74.80	73.15	65.54
Polynomial	33.85	14.64	76.47	41.65	35.76	12.58	75.17	41.17	86.97	28.46	91.22	68.88
Ours	<b>72.61</b>	<b>90.91</b>	<b>92.97</b>	<b>85.50</b>	<b>58.95</b>	<b>90.44</b>	<b>87.81</b>	<b>79.07</b>	<b>89.72</b>	<b>92.97</b>	<b>96.90</b>	<b>93.20</b>

# Experiment



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**Ablation Study**  
① Atomic Visual Space  
② Comorbidity Topology

No.	①	②	mAP $\uparrow$	F1 $\uparrow$	AUC $\uparrow$	Avg. $\uparrow$
#1	$\times$	$\times$	60.73	88.38	88.79	79.30
#2	$\checkmark$	$\times$	70.31	90.00	92.62	84.31
#3	$\times$	$\checkmark$	69.12	90.70	92.42	84.08
#4	$\checkmark$	$\checkmark$	<b>72.61</b>	<b>90.91</b>	<b>92.97</b>	<b>85.50</b>

**Robustness on  
tong-tailed dataset**

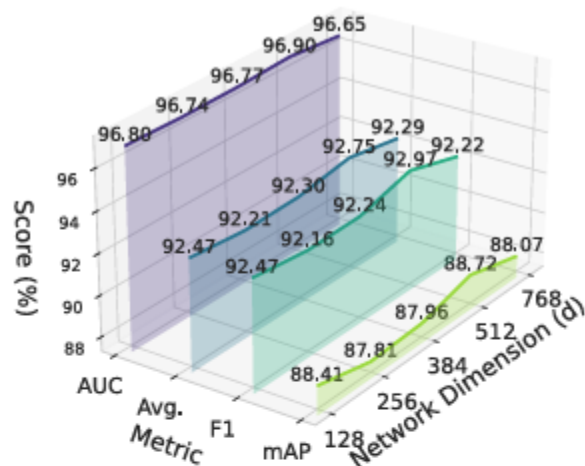
No.	Topo.		Objec.		Groups		
	w	w/o	$\mathcal{L}_{fuzzy}$	$\mathcal{L}_{BCE}$	Head	Middle	Tail
#1	$\checkmark$	$\times$	$\times$	$\checkmark$	<b>74.14</b>	71.13	67.16
#2	$\times$	$\checkmark$	$\checkmark$	$\times$	72.59	68.29	72.87
#3	$\checkmark$	$\times$	$\checkmark$	$\times$	73.83	<b>71.92</b>	<b>74.30</b>

# Experiment

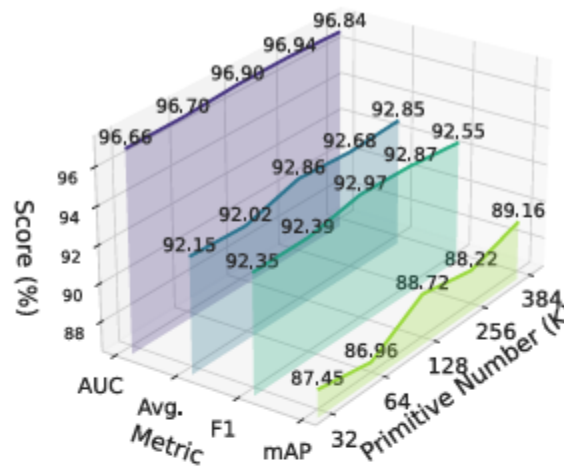


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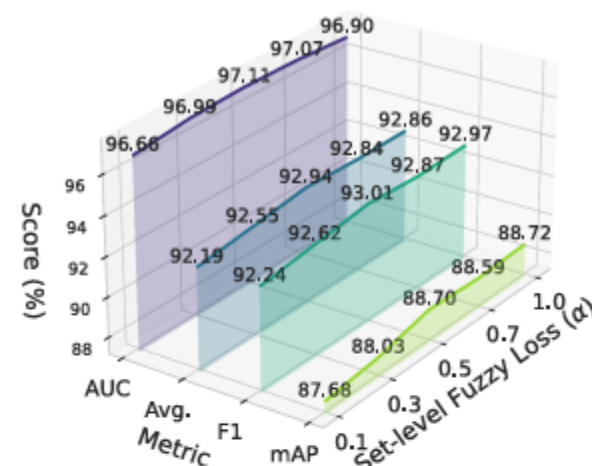
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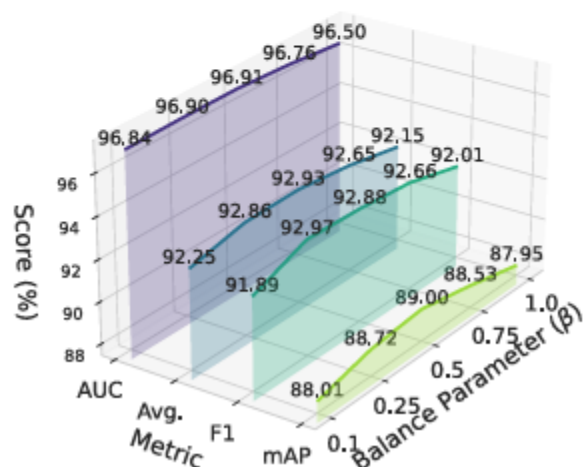
(a)



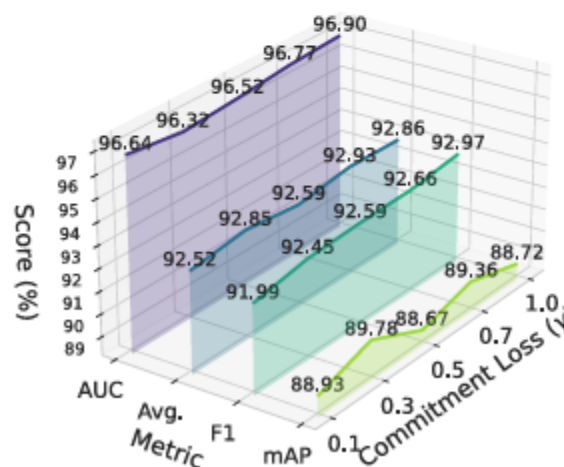
(b)



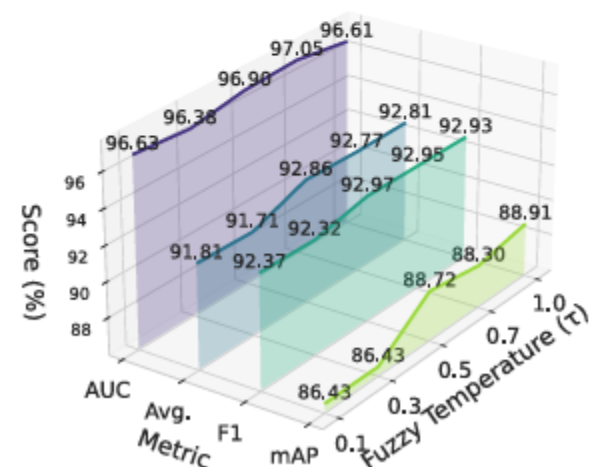
(c)



(d)



(e)



(f)



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