#### **Cross-View Relation Networks for** Mammogram Mass Detection

Jiechao Ma<sup>1</sup>, Xiang Li<sup>1</sup>, Hongwei Li<sup>2</sup>, Ruixuan Wang<sup>1</sup>, Bjoern Menze<sup>2</sup>, Wei-Shi Zheng<sup>1</sup>

<sup>1</sup>Sun Yat-sen University <sup>2</sup>Technical University of Munich







# Background



(a) CC View

Figure 1. Relations between CC view and MLO view [1].

(b) MLO View





#### Motivation

- Radiologists relation reasoning procedure:
  - Extract suspicious regions in the target view;
  - Search the corresponding features in the other view;
  - Combine information and make diagnosis decision under cross-view.

#### How to model clinical experience ?

- The Two-branch Faster RCNNs represent Extract regions in two views of breasts.
- The Cross-view Relation Networks represent Search regions in breasts, enables relational reasoning via iterated, message-passing-like modes of processing.
- The Channel-wise attention module represent Combine cross-view information to reweight the feature maps of different views.

### Our Overall Framework



Figure 2. The architecture of the proposed cross-view relation networks.



### **Quantitative Results**

#### Comparison with state-of-the-art methods:

**Table 1.** Comparisons with state-of-the-art methods with true positive rate (TPR) versus FPI on the public DDSM dataset.

Methods	$F_1$ score	TPR@FPI
Campanini et al. [25]	-	0.80@1.1
Eltonsy et al. [26]	-	0.92@5.4, 0.88@2.4, 0.81@0.6
Sampat et al. [27]	-	0.88@2.7, 0.85@1.5, 0.80@1.0
Li et al. [29]	-	0.90@3.4, 0.87@2.0, 0.84@1.0
Min et al. [3]	-	0.89@2.5, 0.86@1.7, 0.84@1.2
Yan et al. [4]	-	0.87@2.3, 0.76@1.7, 0.73@1.1
Faster RCNN [22]	0.52	0.85@2.1, 0.75@,1.8, 0.73@1.2
two-branch Faster RCNNs	0.57	0.75@1.0, 0.73@0.9
CVR-RCNN	0.75	0.92@2.2, 0.88@1.9, 0.85@1.2

## Ablation Study

**Table 2.** Effect of relation block(s) in the cross-view relation network on the private dataset. N = 0 corresponds to the two branch factor range without relation block

two-pranch taster renns without relation blocks											
two-oranen faster tennis without relation blocks.						$\frac{CCLoss}{MLOLoss}$	$rac{Reg.Loss}{Cls.Loss}$	Precision(%)	Recall(%)	F1-Score	FPI
							2:1	68.18	72.13	0.49	0.40
Relation	<b>D</b> register $(0^{\prime})$	$\mathbf{D}_{\alpha\alpha\alpha} \mathbf{I} (0)$	E Seere	FDI		2:1	1:1	70.69	70.83	0.50	0.36
<b>Block</b> $(N)$	Precision (%)	Recall (%)	$F_1$ Score	<b>FFI</b>			1:2	68.94	72.86	0.50	0.37
						2:1	71.72	75.33	0.73	0.30	
N=0	65.27	71.93	0.69	0.42		1:1	1:1	70.23	74.46	0.52	0.35
N-1	69.66	71 70	0.71	0.35		1:2	71.53	72.71	0.52	0.33	
N = 1	70.10	71.70	0.71				2:1	72.20	71.26	0.51	0.31
N=2	/0.10	72.13	0.71	0.33	1:2	1:1	69.37	71.26	0.49	0.35	
N=3	71.12	75.33	0.73	0.30		1:2	69.76	71.99	0.50	0.36	
N=4	76.56	70.39	0.73	0.27							

**Table 4.** Comparisons with different detection models
 in the cross-view relation network.

Methods	Precision	Recall	$F_1$ Score	FPI					
	(1010)	70 520	0.67	0.45	Methods	Precision	Recall	$F_1$	FPI
Faster RCNN [22]	64.01%	/0.53%	0.67	0.45	Early Engine with DNN [20]	66 7701	67 0201	0.70	0.20
two-branch Faster RCNNs	65.27%	71.93%	0.69	0.42	Early Fusion with KININ [20]	00.77%	07.85%	0.70	0.39
SSD [28]	65.75%	66.91%	0.66	0.42	Later Fusion with FC-layer [19]	66.77%	71.86%	0.69	0.40
two-branch SSDs	66.40%	68.30%	0.67	0.41	Individual-similar-param	67.37%	71.73%	0.69	0.40
CVR-RCNN	71.12%	75.33%	0.73	0.30	CVR-RCNN	71.12%	75.33%	0.73	0.30

**Table 3.** Effect of design loss in the cross-view relation network.

**Table 5.** Comparisons with different modify models in the
 cross-view relation network.

![](_page_6_Figure_8.jpeg)

#### Visualization

![](_page_7_Picture_1.jpeg)

Fig.3. Exemplar mass detection results by the proposed method. First pair: MLO

and CC view of a right breast. Second and third pairs: MLO and CC view of two left breasts. Green boxes represent detection results, while red boxes for ground-truths.

Thank you!