

Introduction

Background

The pathological information from the two paired views (i.e., medio-lateral oblique and cranio-caudal) are highly relational and complementary, which is crucial for diagnosis in clinical practice.

How to model clinical experience ?

Motivation: Radiologists take the reasoning procedure explicitly: 1. Extract suspicious regions in the examined view; 2. Search the regions in the other view to make comprehensive decisions.

Proposed method: We imitate this process and propose to extract discriminating correlative features, using relation agent to operate two views' complementary information, structuring representations via iterated, message-passing-like modes of processing.

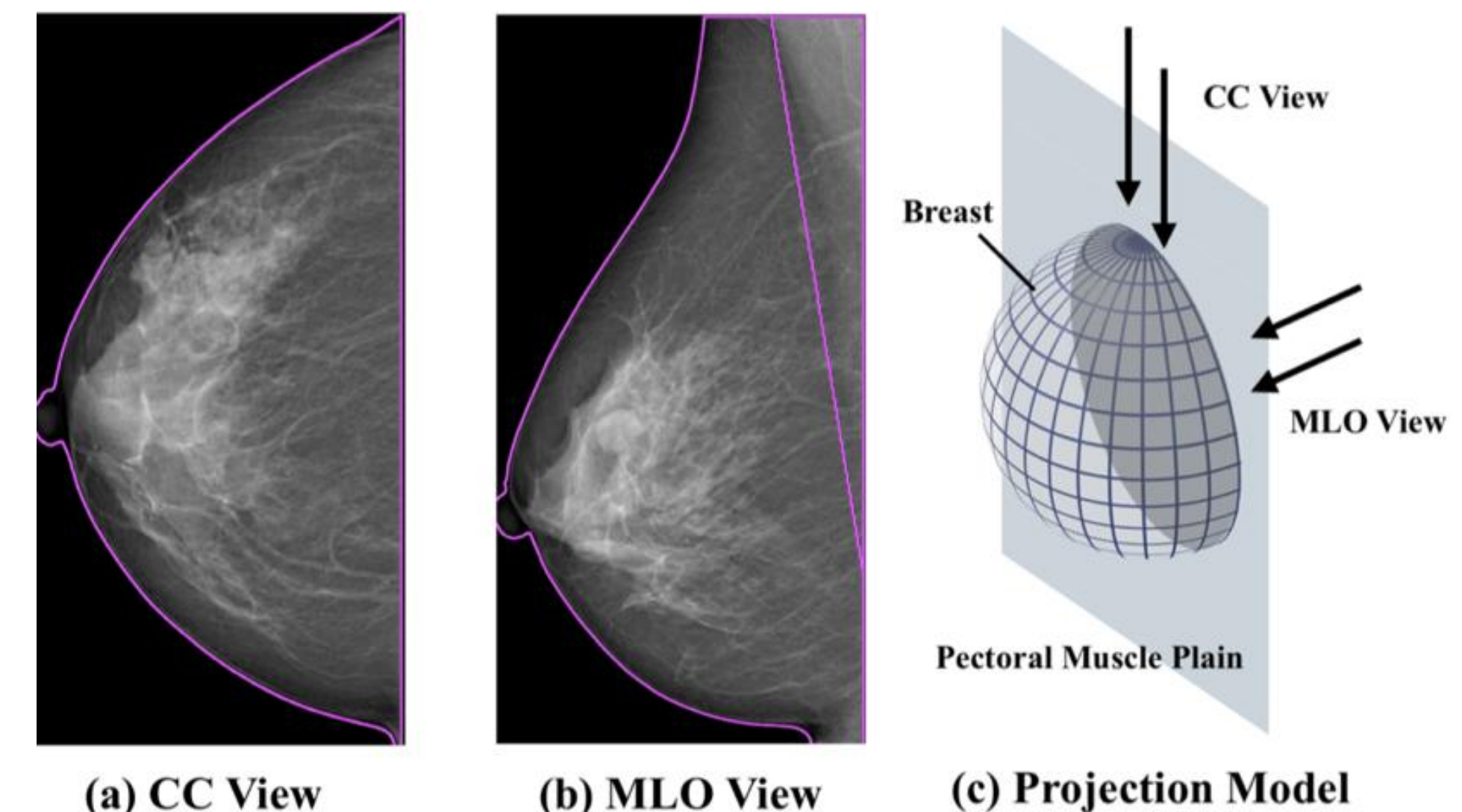


Fig.1. The cross views contain a CC view and an MLO view. CC view (a) is top-down view, while MLO view (b) is a side view taken at a certain angle. (c) shows an ideal projection model [1].

Methodology

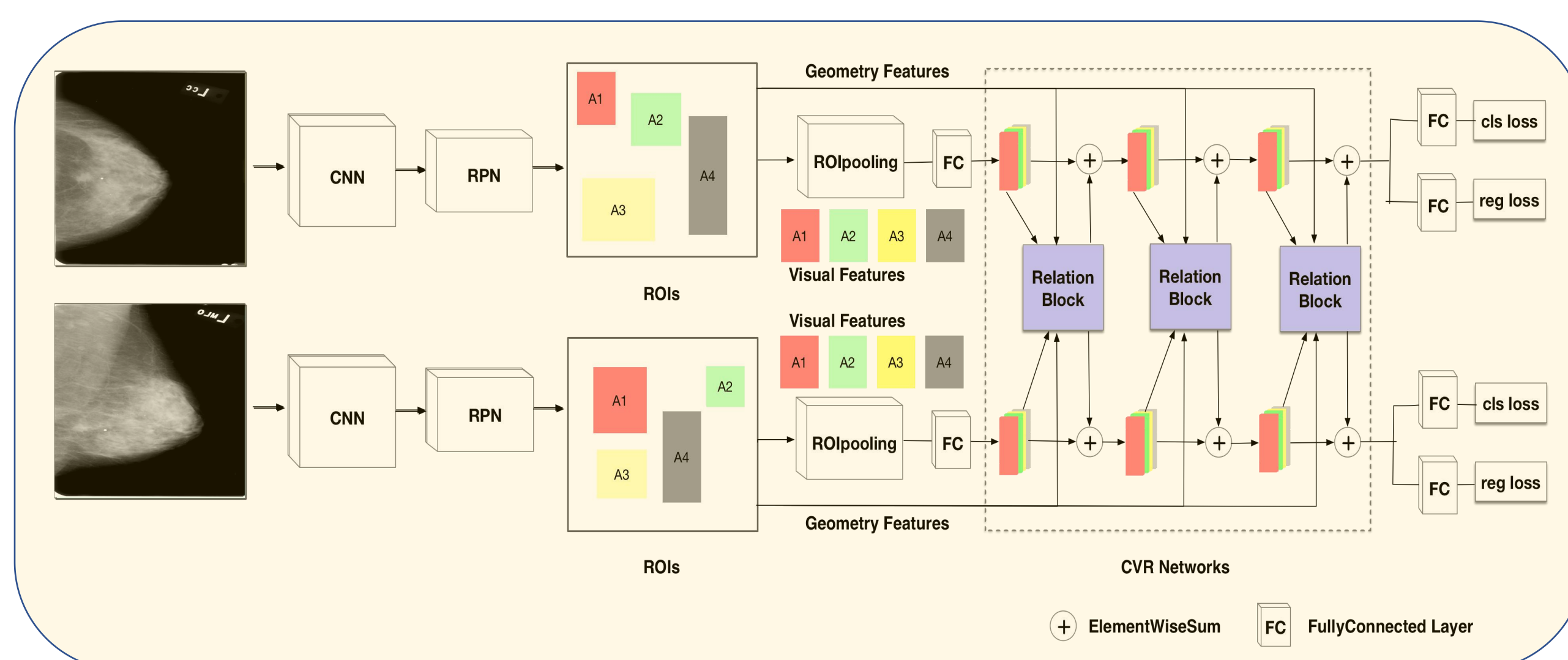


Fig.2. The architecture of our CVR-RCNN framework. A paired input image set is fed into the two-branch Faster RCNNs to get the ROIs. The visual and geometry features of ROIs are used by cross-view relation network to learn the effective relation features.

Two-branch Faster RCNNs: A two pathway architecture is applied to extract the discriminating correlative features from each representative view. The backbone network adopt two weight-shared Faster-RCNN connected by several relation blocks.

Cross-view Relation Networks: The objective of the relation network is to transfer both *semantic* and *geometric* information of ROIs from the second (or first) view to the first (or second) one to help detect masses more effectively.

Channel-wise attention module: A channel-wise attention based feature aggregation mechanism that supervised by classification loss to reweight the feature maps of different views.

Experiments

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

Table 2. Effect of relation block(s) in the cross-view relation network on the private dataset. $N = 0$ corresponds to the two-branch faster rcnns without relation blocks.

Relation Block (N)	Precision (%)	Recall (%)	F_1 Score	FPI
$N=0$	65.27	71.93	0.69	0.42
$N=1$	69.66	71.70	0.71	0.35
$N=2$	70.10	72.13	0.71	0.33
$N=3$	71.12	75.33	0.73	0.30
$N=4$	76.56	70.39	0.73	0.27

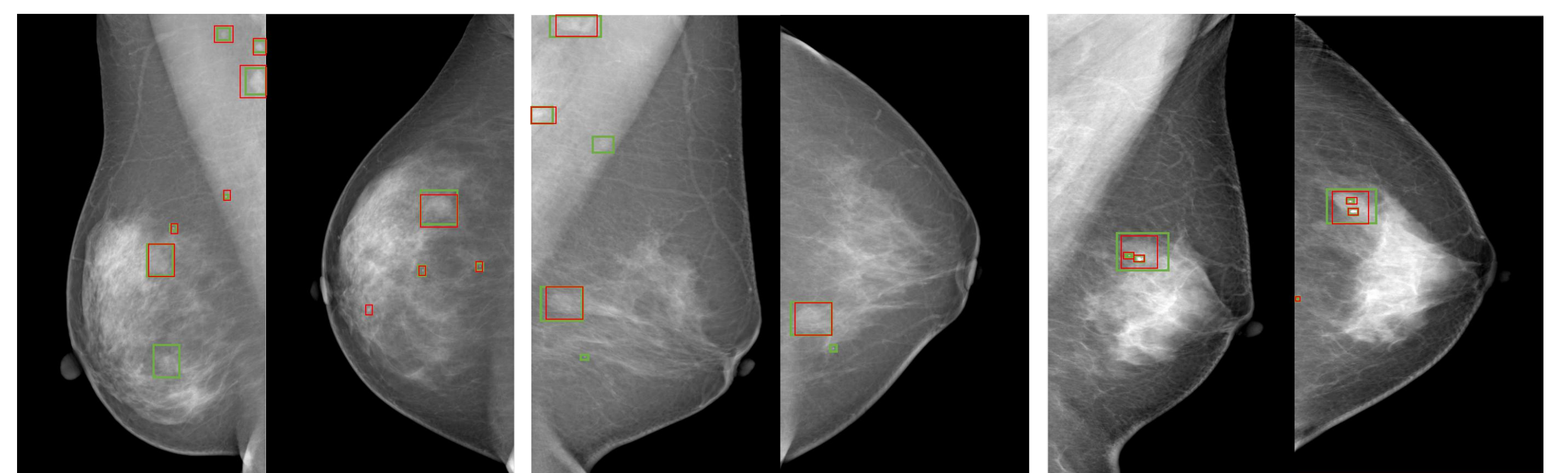


Fig.3. Exemplar mass detection results by the proposed method. First pair: MLO and CC view of a right breast. Second and third pairs: MLO and CC view of two left breasts. Green boxes represent detection results, while red boxes for ground-truths.

Table 3. Effect of design loss in the cross-view relation network on the private dataset.

$\frac{CCLoss}{MLOLoss}$	$\frac{Reg.Loss}{Cls.Loss}$	Precision(%)	Recall(%)	F1-Score	FPI
2:1	2:1	68.18	72.13	0.49	0.40
	1:1	70.69	70.83	0.50	0.36
	1:2	68.94	72.86	0.50	0.37
1:1	2:1	71.72	75.33	0.73	0.30
	1:1	70.23	74.46	0.52	0.35
	1:2	71.53	72.71	0.52	0.33
1:2	2:1	72.20	71.26	0.51	0.31
	1:1	69.37	71.26	0.49	0.35
	1:2	69.76	71.99	0.50	0.36