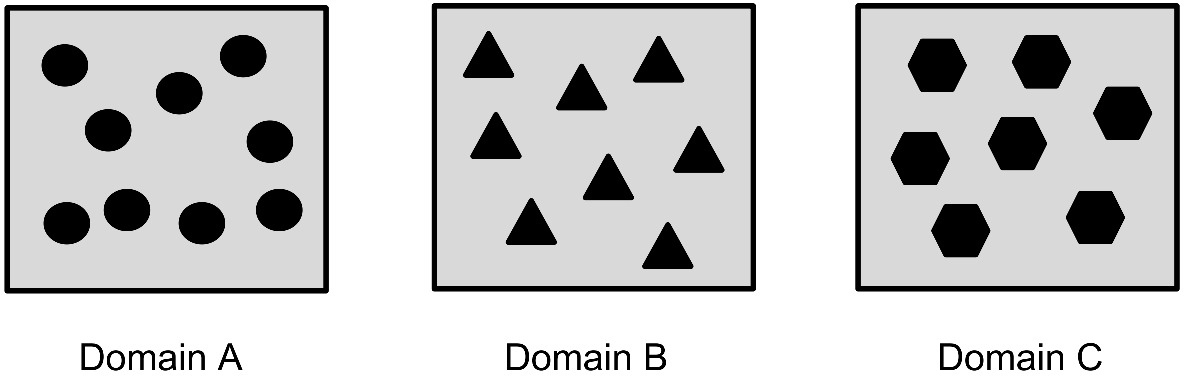
AN END-TO-END NETWORK for DETECTING MULTI-DOMAIN FRACTURES on X-RAY IMAGES

Motivations



We need consider:

Private features inside each domain

Common features of all the domains

How to choose a model?

Solution 1

Train a model for each domain

Challenges

Require storage space, training time and a classification model

Solution 2

Train a model on all the domains

Challenges

Do not consider private features of each domain

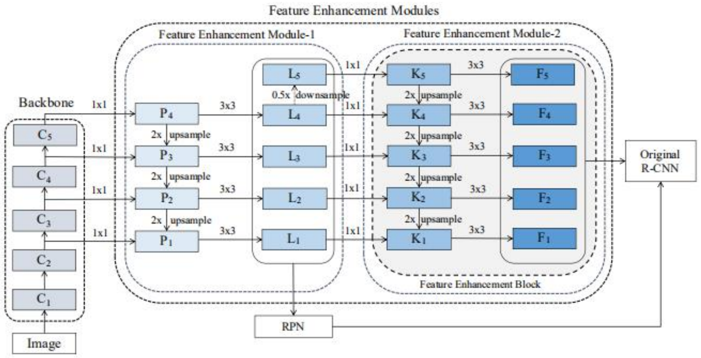
Contributions

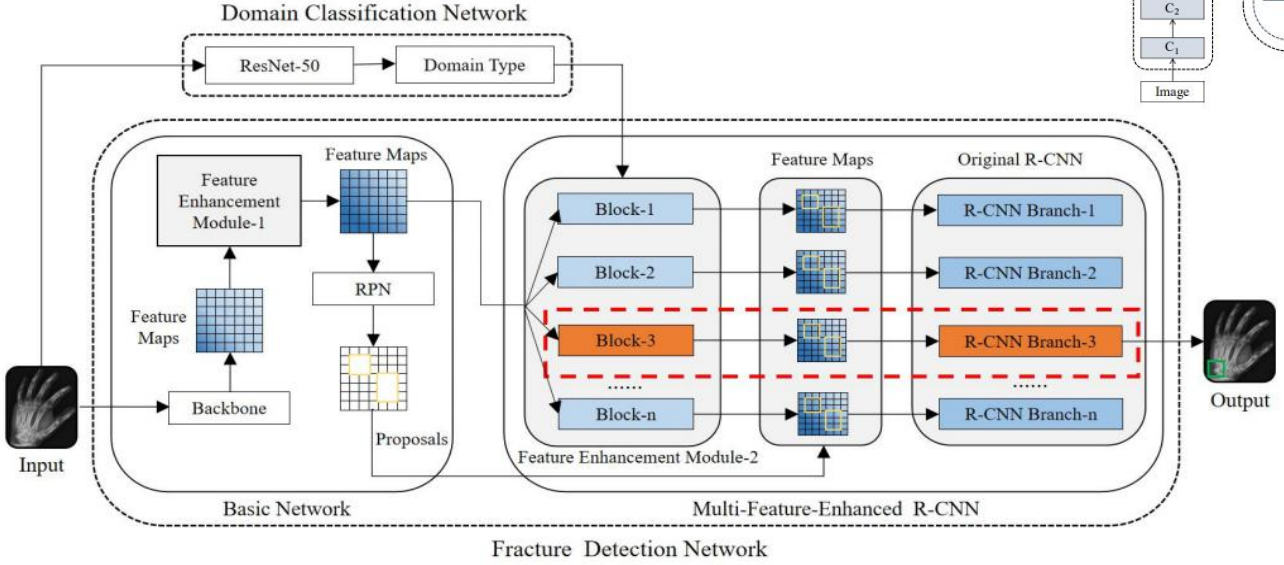
1. We are the first to focus on the multi-domain problems of fracture detection and utilize a novel end-to-end model to improve the performance.

2. We propose Feature Enhancement Modules and introduce Muti-Feature-Enhanced R-CNN to learn better feature representations for each domain.

3. Experimental results on real-world datasets demonstrate the effectiveness of our model.

Network





$$Loss = Loss_{RPN} + \alpha \cdot Loss_{R-CNN} + \beta \cdot Loss_{domain}$$

Dataset

Table 1. The number of images from each domain.

Domain	HW	FA	EK	Total
Train	2,429	1,899	270	4,598
Test	603	473	65	1,141
Total	3,032	2,372	335	5,739

Classification Performance

Table 2. The classification performance on different domains.

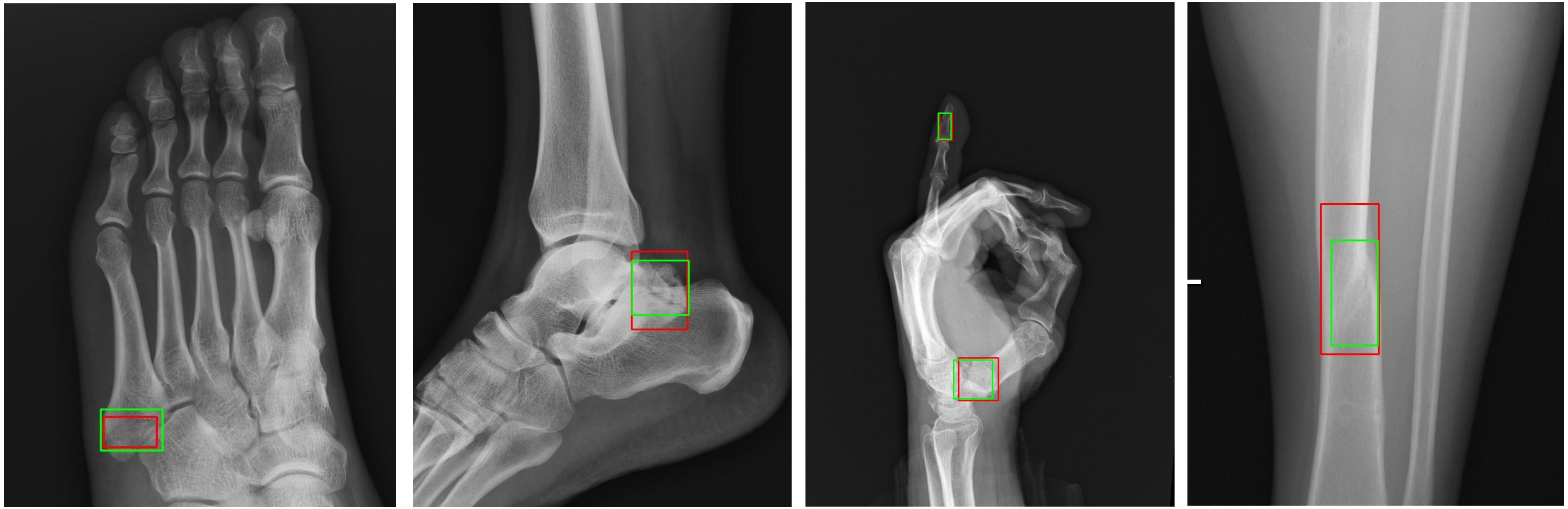
Domain	HW	FA	EK
Accuracy(%)	99.34	99.37	98.46

Detection Performance

Table 3. The detection performance on different domains. Multiple R-CNN represents multiple original R-CNN branches.

Methods	HW			AF			EK		
	P(%)	R(%)	F	P(%)	R(%)	F	P(%)	R(%)	F
Faster R-CNN	**88.4**	21.6	0.347	79.2	19.0	0.307	71.4	27.2	0.394
Faster R-CNN + Multiple R-CNN	88.0	20.9	0.338	77.0	19.4	0.310	77.3	37.0	0.500
Faster R-CNN + FEM-1	80.5	71.8	0.759	78.2	72.4	0.752	79.8	77.2	0.785
Faster R-CNN + FEM-1 + FEM-2	82.4	72.1	0.769	79.3	**72.6**	0.758	80.4	77.9	0.791
MFDN	81.2	**74.4**	**0.777**	**81.3**	**72.6**	**0.767**	**81.8**	**78.3**	**0.800**

Experimental Results



END

Thanks for Listening