

# Fully Convolutional Networks for Surface Defect Inspection in Industrial Environment

## 一、主要贡献

1. 提出了一种用于工业的表面缺陷检测的可复用，高效的二阶段方法。目标是为了达到效率和准确度的平衡。

## 二、动机

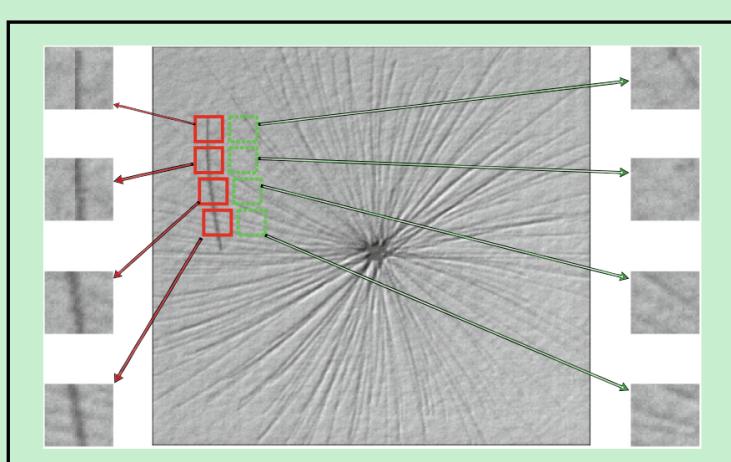
缺陷检测的传统方法基本上都是基于特征提取+分类器的思路。这种方法的缺点是需要进行人为的特征提取，繁琐耗时。而目前的深度学习方法可以自动提取特征，因此本文考虑使用深度学习方法来解决缺陷检测的问题。具体来说，考虑到缺陷检测实际上可以当做是语义分割的问题，因此本文提出了一种两阶段的FCN算法，来实现缺陷检测。

## 三、方法

### 假设

在讲具体的方法之前，需要对数据做一个假定：

局部信息或者说缺陷区域的一个小块能够表明缺陷的存在，并且缺陷检测过程和缺陷区域的几何形状没有很大的关系。这个假设意味着缺陷不是一个常规物体，常规物体的几何信息和全局信息在检测中是非常重要的。



**Fig. 2.** A schematic diagram of patches cropped from images. The red-solid-line rectangles illustrate patches cropped from defect areas and the green-dotted-line rectangles illustrate patches cropped from non-defect areas (Color figure online)

### 数据生成

从原始图像中截取 $32 \times 32$ 或者 $64 \times 64$ 大小的图像块，步长分别为16和64。经过这个操作，150张训练图片就可以得到16000张图片。

### 阶段一

阶段一的目标是对缺陷区域（也叫做ROI）进行一个快速但是相对粗糙的检测。ROI的预测结果可以用于阶段二，限制阶段二的搜索范围。最终的目的是为了改善效果。

问题：

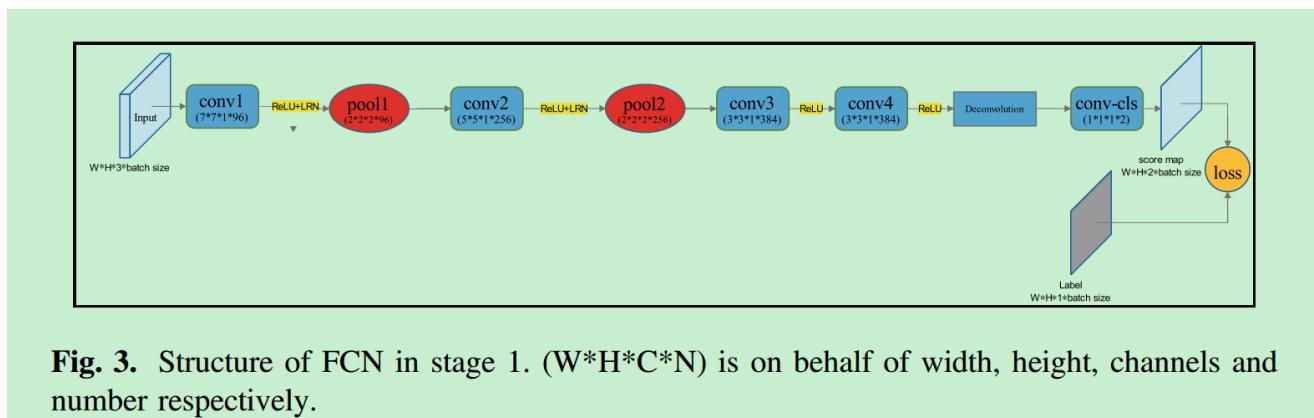
如果用一个现成的FCN网络来进行语义分割在缺陷检测的任务中可能并不是合适。因为：

1. FCN是一个比较深的网络，训练的数据量很大，类别很多，但是缺陷检测中通常数据量很少，因此很可能导致过拟合。
2. ImageNet预训练的网络直接迁移到缺陷检测中可能并不合适，因为ImageNet是自然图片，而缺陷图片和自然图片差异通常很大。

基于以上两个考虑，作者提出需要寻找一个合适的网络和合适的训练策略避免过拟合。

FCN架构

FCN网络使用了ZF的前面4层。训练阶段，使用图像块进行训练，测试阶段，使用整张图像进行测试。



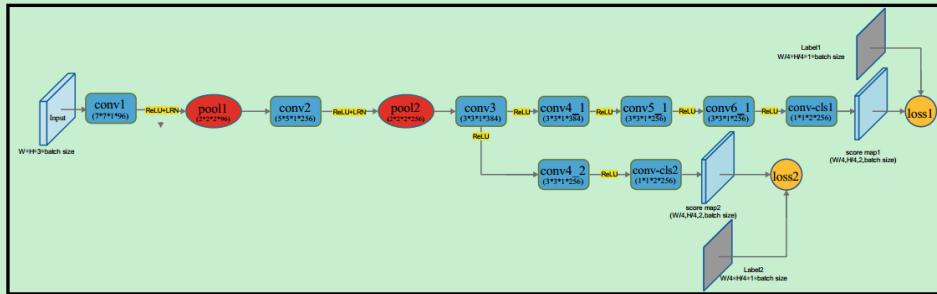
**Fig. 3.** Structure of FCN in stage 1. ( $W \times H \times C \times N$ ) is on behalf of width, height, channels and number respectively.

## 阶段二

### Segmentation Refinement with Instance-Sensitive Patches

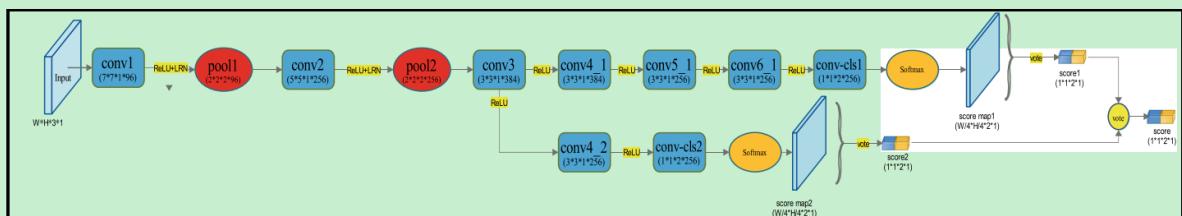
阶段二是对分割结果的微调。第一阶段主要把注意力集中在了局部信息，但是物体级别的信息对分割一个缺陷区域来说也很重要，也就是说，某块区域是不是缺陷区域在缺陷检测中是一个重要的信息。因此阶段2主要在物体级别上去改善阶段一的结果。阶段二仍然使用阶段一从原始图像上切下来的图像块，但是阶段二的任务是检测这个块是否是缺陷区域而不是分割。因此，训练的时候，图像的label不是分割的label。对那些和整个缺陷区域的重叠度达到n%（本文中n=40）的缺陷区域当做缺陷区域，否则就当做非缺陷区域。

阶段二的网络结构如下图，该网络设置了多损失。网络输出的score map要么全是0要么全是1。



**Fig. 5.** Multi-loss-function structure of FCN in stage 2. ReLU is the activation function and LRN is short for local response normalization layer.

在检测阶段：

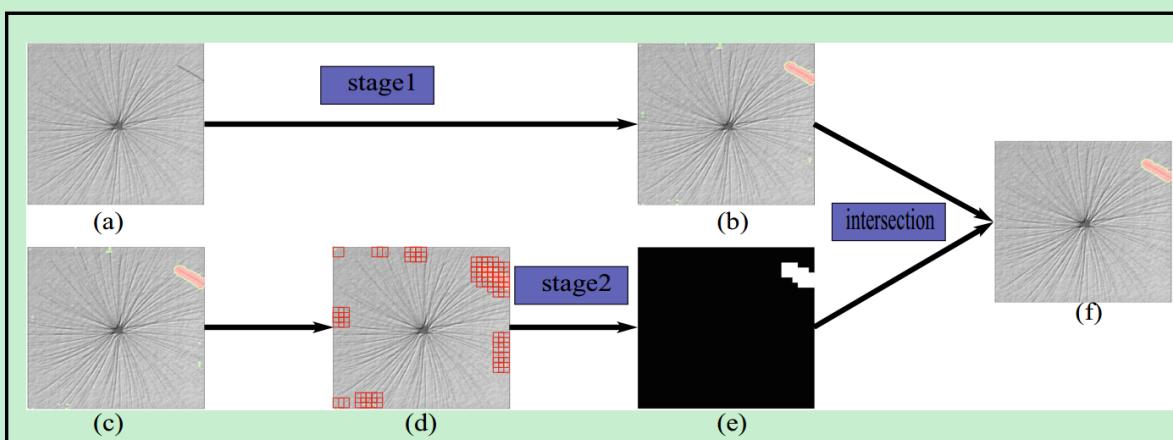


**Fig. 6.** Illustration of inspection process. Score1 and score2 is the mean value of each corresponding score map and score is the average number of score 1 and score 2.

将网络的输出scope map进行平均，得到1x1的输出。再求一次平均，得到最终结果。实际上就是一种多尺度检测的思想。

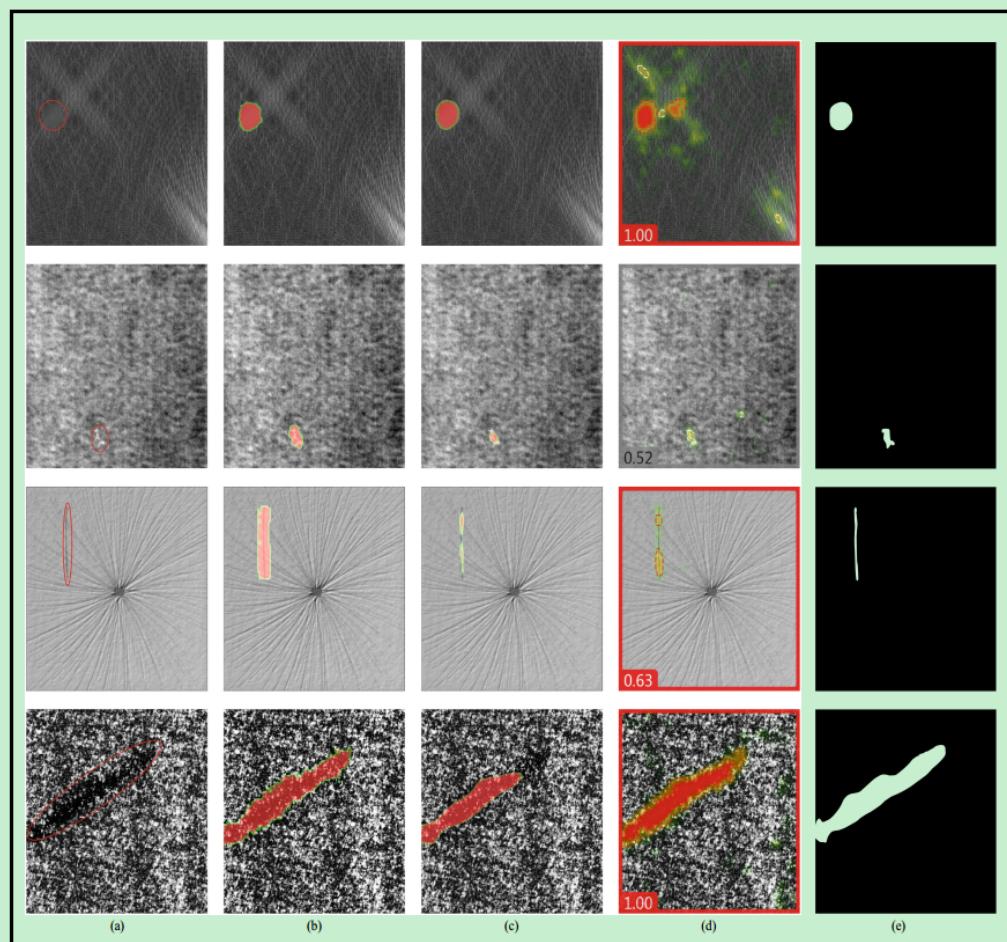
## 两个阶段的整合

将分割和检测进行整合，得到最终的结果。



**Fig. 4.** Fusion of stage 1 and stage 2. (a) is the original image to be inspected, (b) is the coarse segmentation result of stage 1 and this result is also the initialization of stage 2 (numbered as (c)), (d) shows the patches cropped around the ROIs from stage 1. (e) is the detection result of stage 2, each patch is classified into either defect patch or non-defect one. (f) is the intersection of stage 1 and stage 2, (f) is also the final inspection result.

## 四、实验结果



**Fig. 7.** Results comparison: (a) Initial input images. (b) Results of ours. (c) Results of FCN (d) Results of ViDi. (e) Ground truth.

**Table 1.** Overall performance of segmentation

Inspector	Mean accuracy	Time for inspection (512*512 input)
FCN(voc-fcn32s) [7]	79.3547%	71 ms
FCN(voc-fcn16s) [7]	90.0371%	75 ms
FCN(voc-fcn8s) [7]	92.2488%	78 ms
ViDi [11]	93.7488%	20 ms
Ours(stage 1)	95.9830%	48 ms
Ours(stage 2)	<b>95.9934%</b>	20–50 ms

# Vision-Based Defect Detection for Mobile Phone Cover Glass using Deep Neural Networks

## 一、主要内容：

1. 对Mobile Phone Cover Glass进行缺陷检测。
2. 改进的深度学习分割方法用于缺陷检测。

## 二、数据示例

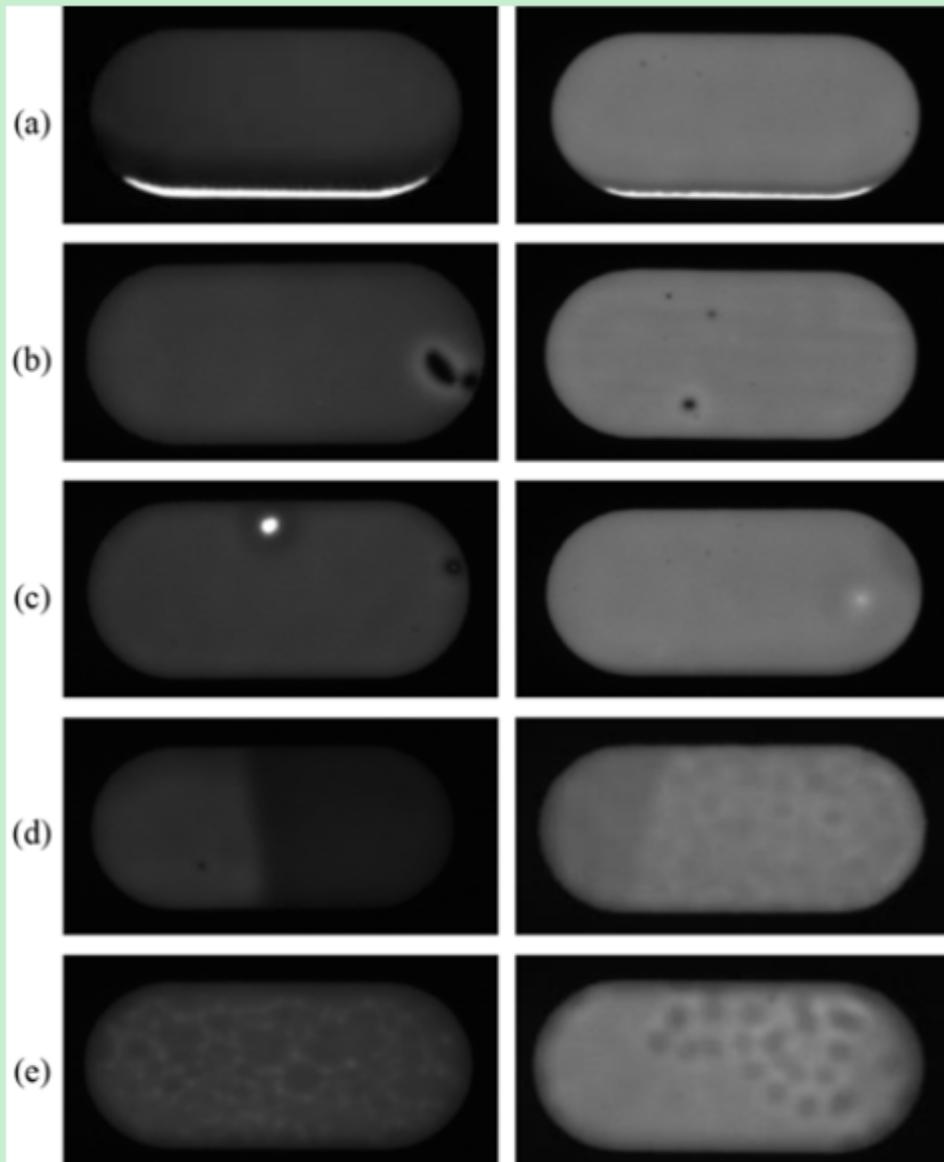


Fig. 4 Typical defects of IR hole. The defects can be generally classified into (a) miss printing (b) black point (c) white point (d) contrast color and (e) peel-like appearance. The images illustrate the imaging inconsistency. The first column show the IR images with lower gray intensities while the second column are the ones with higher intensities

### 三、动机

传统方法很难表达缺陷的形态学和成像不连续性。因此考虑使用深度学习方法。但深度学习方法也有限制，比如：

1. 需要大量数据，因此提出一个数据生成的方法。
2. 采用语义分割进行检测，受到对抗分割思想的启发，本文使用对抗学习设计了一个分割网络，使得结果更有鲁棒性。

### 四、模型

考虑到pooling会降低分辨率，同时为了保持网络的感受野，本文使用Dilated conv进行构建网络。模型的设计如下：

Layers	1	2	3	4	5	6	7	8
Name	Conv_1	Pool_1	D-conv_1	D-conv_2	D-conv_3	D-conv_4	D-conv_5	Conv_2
Dilation size	1		2	2	4	4	8	1
Kernel size	3×3		3×3	3×3	3×3	3×3	3×3	3×3
Kernel receptive field	3×3		5×5	5×5	9×9	9×9	17×17	3×3
Kernel receptive field w.r.t. Pool_1			3×3	3×3	5×5	5×5	9×9	2×2
Receptive field w.r.t. Pool_1			3×3	5×5	9×9	13×13	21×21	22×22
Receptive field	3×3	4×4	12×12	20×20	36×36	52×52	84×84	88×88

网络的前五层：

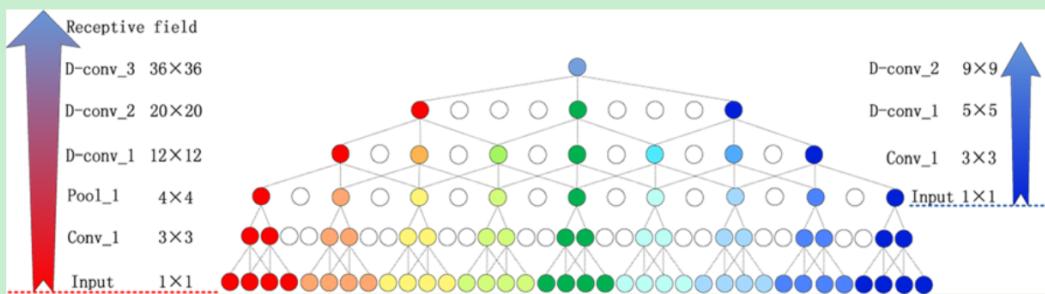


Fig. 7 The first 5 layers of our network. The axis left computes receptive fields from the input layer while the right one only focuses on dilated layers. Conv, Pool, and D-conv respectively represent the convolutional layer, pooling layer and dilated convolutional layer. The right axis illustrates the receptive field size of the output layer w.r.t. Pool\_1

另外，网络输出是二值化的输出，也就是说不分缺陷类型。

### 五、对抗训练

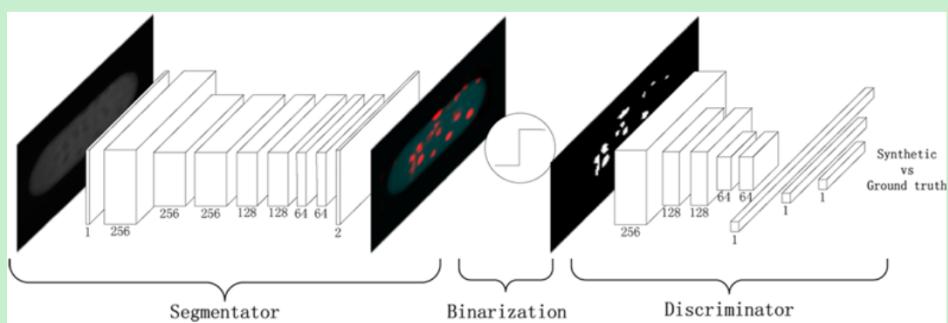


Fig. 6 The abridged general view of the defect segmentation model training with the adversarial network. The segmentor uses the standard segmentation method that gives out synthetic label maps. The adversarial network estimating the probability of the label map belonging to ground truth is a CNN-based discrimination network. The input of adversarial network is a collection of binary map acquired from both synthetic label maps and the ground truths

因为分割网络的输出是二值化的，因此损失函数是一个二值交叉熵损失：

$$L(\hat{y}, y) = -\sum_{i=1}^{H \times W} [\hat{y}_i \ln y_i + (1-\hat{y}_i) \ln (1-y_i)]$$

本文的分割架构使用到了对抗分割的思想。

分割模型用S表示，判别器用D表示。S的目标是产生分割结果来欺骗D，而D的目标则是将S的预测和GT区别开来。

$$L = \{-\sum_{i=1}^{H \times W} [\hat{y}_i \ln y_i + (1-\hat{y}_i) \ln (1-y_i)]\} - \lambda \{-[\hat{z} \ln z + (1-\hat{z}) \ln (1-z)]\}$$

## 六、实验

Table 2 Segmentation accuracy on the manual labeled dataset

	Mean IoU	Pixel acc.	Classify acc.
Dilated segmentation	55.94%	97.41%	96.52%
Adversarial segmentation	68.68%	98.80%	98.26%

# A Fast Detection Method via Region-Based Fully Convolutional Neural Networks for Shield Tunnel Lining Defects

## 1. 数据

地铁轨道的数据 : Tunnel lining defects

数据采集过程 :



**Fig. 1.** MTI-100 subway tunnel inspection.



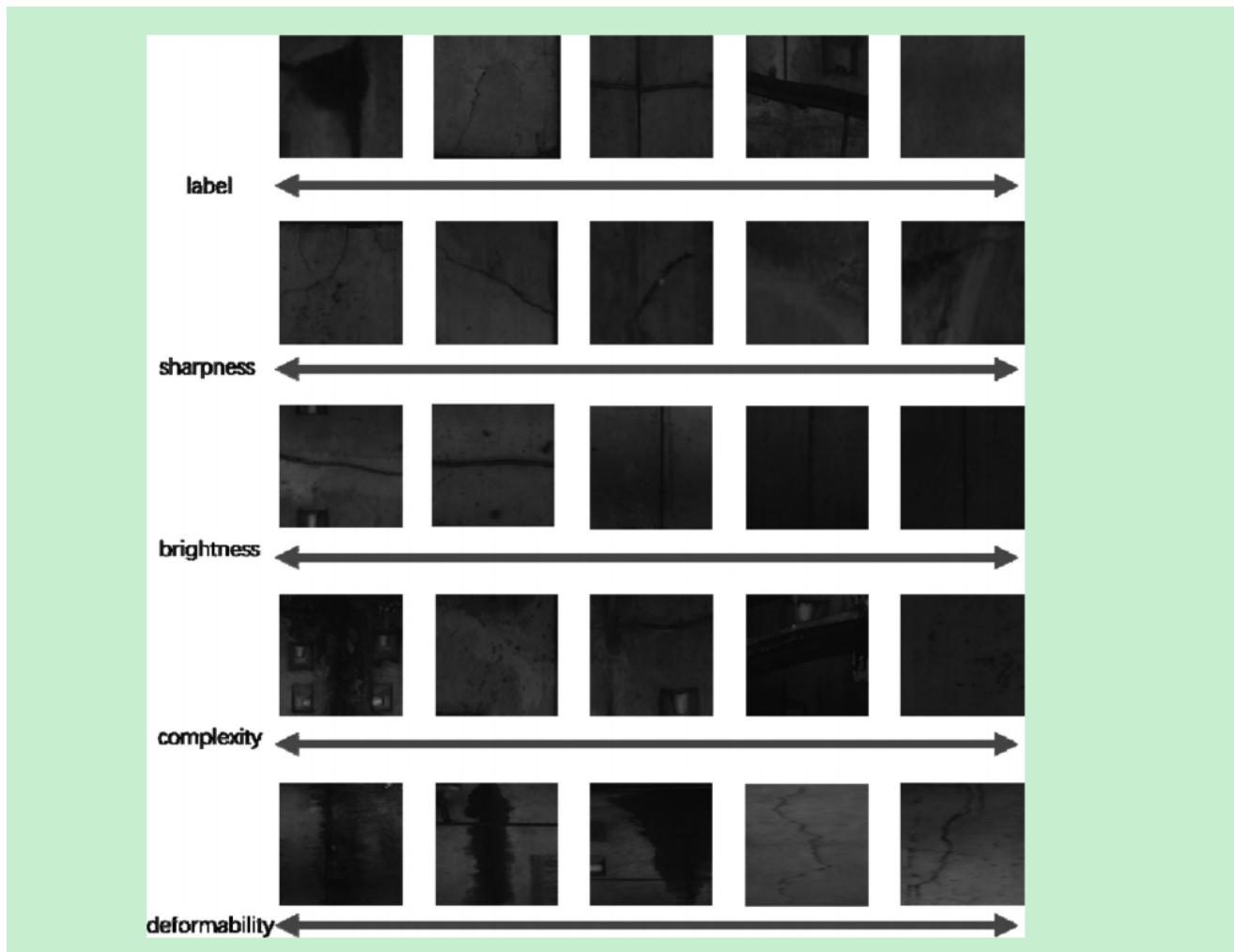
**Fig. 2.** Original lining image samples.

缺陷种类 :

**Table 1**  
Data sets for image classification

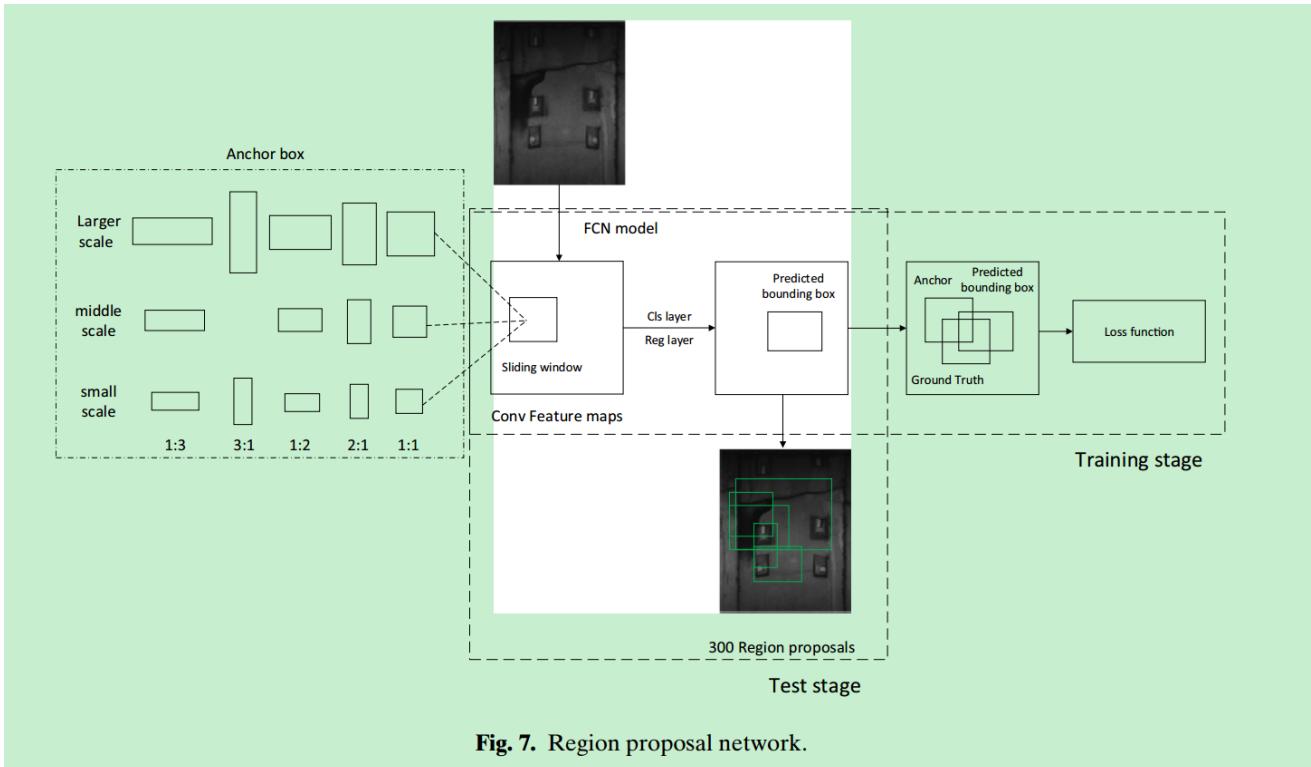
	<i>Label</i>	<i>Training set</i>	<i>Test set</i>	<i>Total</i>
Leakage	1	1,200	400	1,600
Crack	2	1,680	560	2,240
Segment joint	3	1,500	500	2,000
Pipeline	4	1,350	450	1,800
Lining	5	1,410	470	1,880
<b>Sum</b>		<b>7,140</b>	<b>2,380</b>	<b>9,520</b>

缺陷多样性：

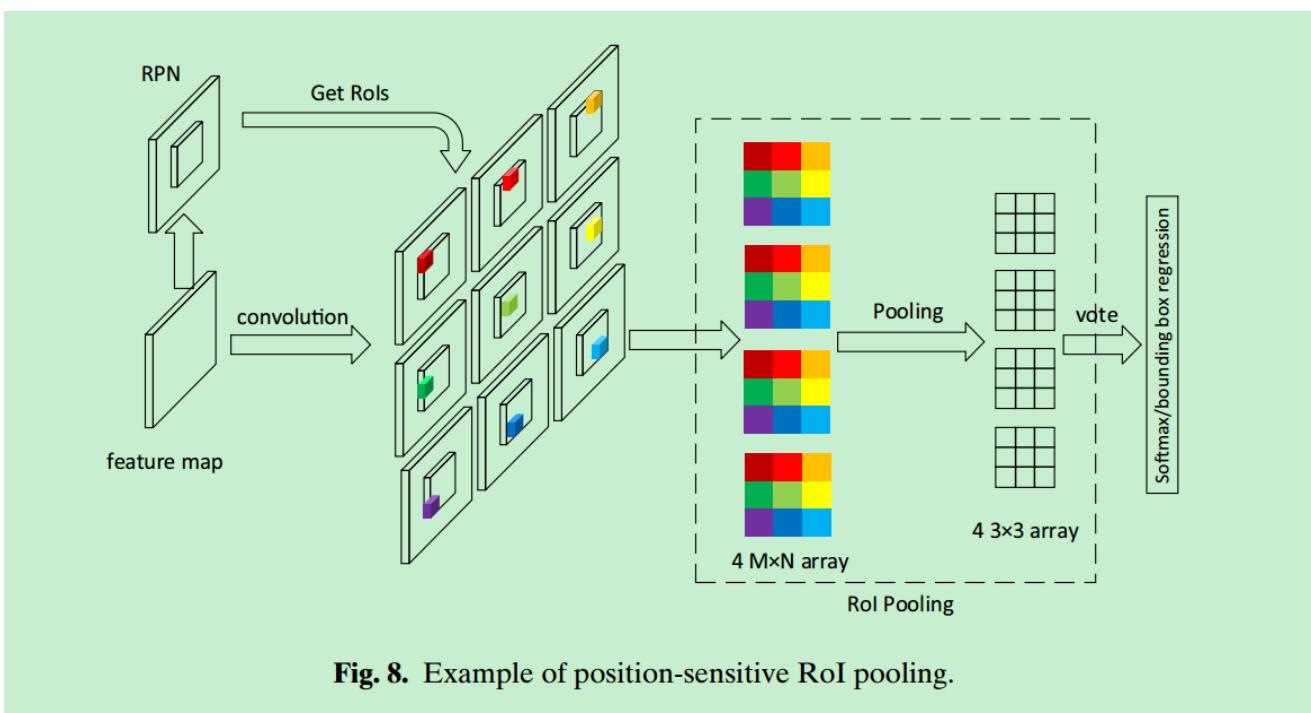


## 2. 检测方法

本文采用R-FCN的方法，另外也和faster RCNN的检测结果进行对比：



**Fig. 7.** Region proposal network.



**Fig. 8.** Example of position-sensitive RoI pooling.

### 3. 实验结果

**Table 7**  
Comparison of the results with the traditional method and Faster R-CNN

Method	Detection rate	Detection accuracy	Detection efficiency	$\eta_1$	$\eta_2$
Proposed method	94.4%	86.6%	0.266 s	0.874	0.062
Faster R-CNN	94.0%	87.3%	0.396 s	0.803	0.125
Traditional method	49.5%		63.340 s	0.646	0.227

# Automatic Localization of Casting Defects with Convolutional Neural Networks

## 数据

检测元件：金属铸件

图像获取：X-ray

红色框区域表示缺陷区域。

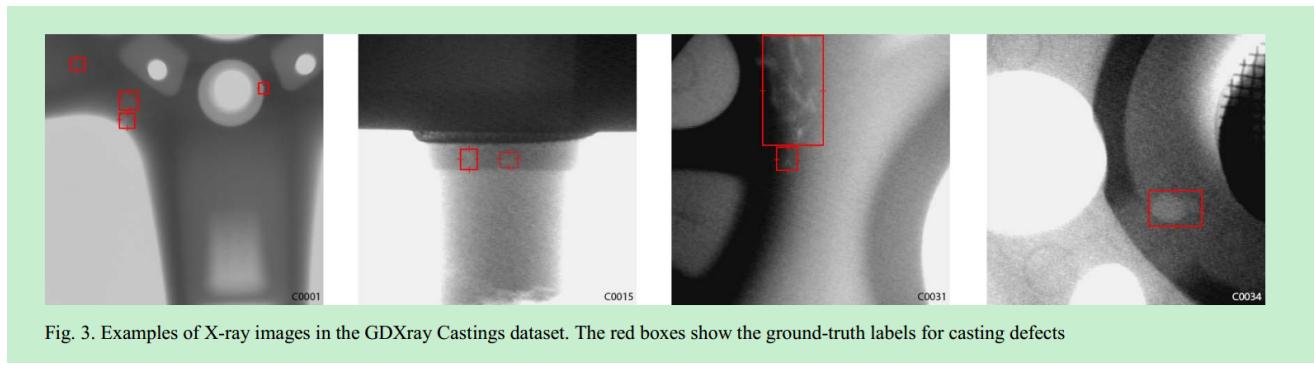


Fig. 3. Examples of X-ray images in the GDXray Castings dataset. The red boxes show the ground-truth labels for casting defects

## 模型

Faster RCNN

SSD

R-FCN

## 实验

训练损失：

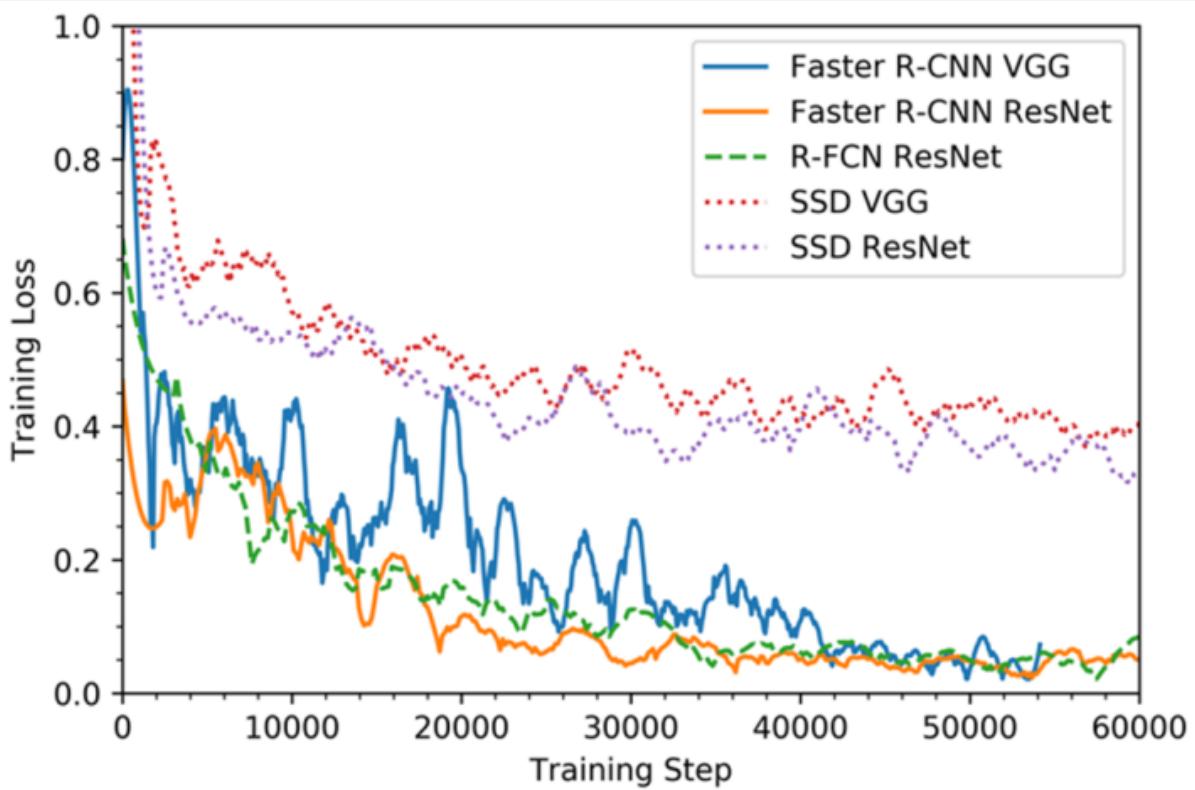


Fig 4. Training loss (smoothed) for the object localization networks, during the fine-tuning process. Note that the loss function for the SSD network varies from that of the R-FCN and Faster R-CNN networks, so the relative magnitudes of loss is not relevant.

mAP和训练数据集大小的关系

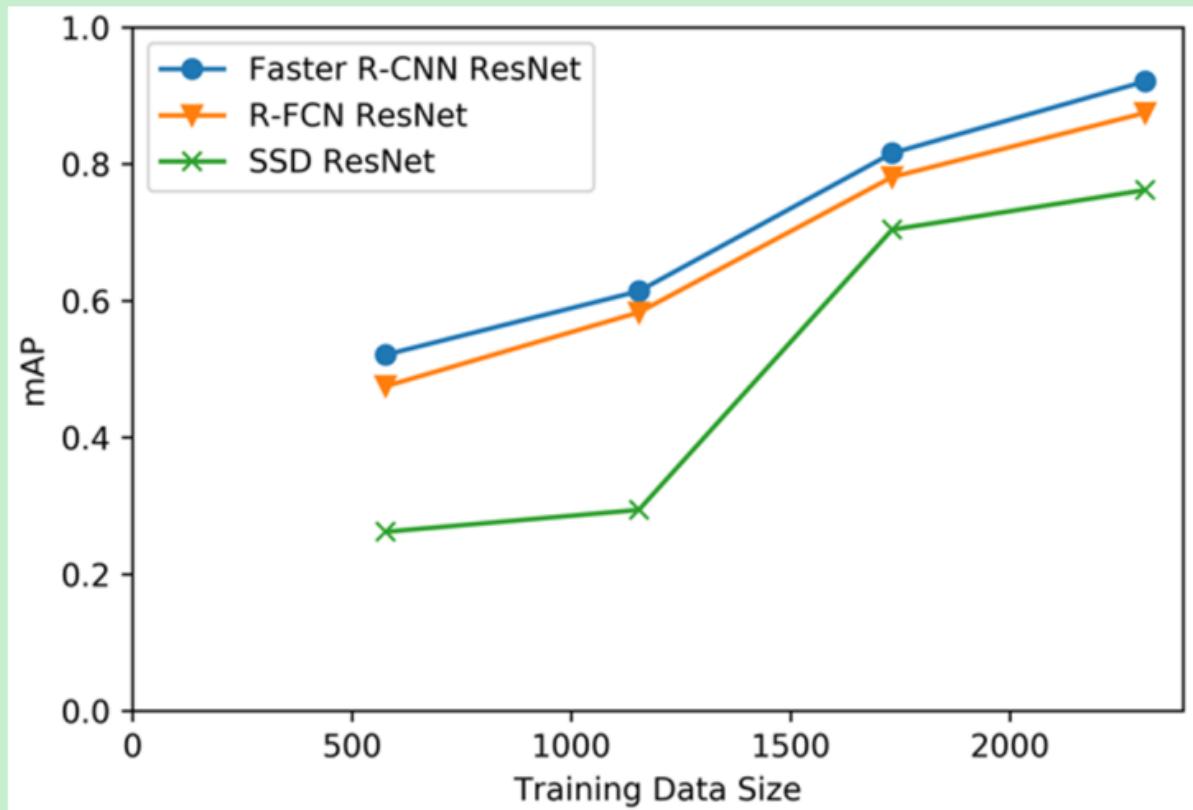


Fig. 5. Mean average precision (mAP) of each object detection network on the test set, given different sized training sets.

实验结果对比：

TABLE III. COMPARISON OF THE ACCURACY AND PERFORMANCE OF EACH MODEL ON THE CASTING DEFECT LOCALIZATION TASK

Method	Evaluation time / image using CPU [s]	Evaluation time / image using GPU [s]	mAP
Sliding window method	2.231	0.231	0.461
Faster R-CNN VGG-16	7.291	0.438	0.865
Faster R-CNN ResNet-101	9.319	0.512	<b>0.921</b>
R-FCN ResNet-101	3.721	0.375	0.875
SSD VGG-16	<b>0.088</b>	<b>0.025</b>	0.697
SSD ResNet-101	0.141	0.051	0.762

## 其他文章

分类：

A Generic Deep-Learning-Based Approach for Automated Surface Inspection

目标检测：

A New Method in Wheel Hub Surface Defect Detection: Object Detection Algorithm Based on Deep Learning

无监督缺陷分类：

# Defects Detection Based on Deep Learning and Transfer Learning