Fabric Defects Detection Based on Faster R-CNN

defectNet: An Efficient Defects Detection Model

defectNet: Towards Efficient Defects Detection

defectNet: Towards Efficient Objects Detection for Defects

Defects Detection Based on Classification and Detection Network

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**Abstract. pass**

**Keywords:**

**Pass**

# Introduction

（背景：）近几年来，深度卷积神经网络在目标检测领域取得了巨大的成功，涌现出了一大批的优秀的检测框架，例如，多阶段的基于区域推荐的（Faster R-CNN）、单阶段直接SSD、YOLO等，他们大都集中于建立一个统一通用的物体检测框架，并且有着较高的准确率和效率，他们虽然能满足大多数物体检测领域的需要，（抛出问题：）但是，在小部分物体检测领域，尤其是在工厂瑕疵检测中，例如，纺织品瑕疵检测，我们不仅仅只关注于一张图像中某个对象的识别和定位，同时我们还需要对该图像是否包含瑕疵对象进行判决，即图像分类问题，甚至有时候对瑕疵进行判决比对物体检测更加重要，因为更高的对瑕疵的判决能力意味着更小的计算成本和更低的错误率，这能降低大量的经济成本。虽然我们也能够利用（state-of-the-art）业界前沿的检测框架解决这些问题，但是他们并不完美，他们对瑕疵的判决能力仍然取决于某个阈值，而这往往会容易受到主观方面的影响，这种情况下他们产生错误的概率仍然很高，所以我们还有可以改进和提升的空间。从另一方面讲，当然，我们可以先训练一个图像分类网络，先对图像是否包含瑕疵进行判决，然后再训练一个目标检测网络，再检测出图像中的瑕疵对象，但是这样太繁琐了，会带来更多的时间和计算成本，因此（hence），我们希望有一个框架能一次性解决上述问题。

在这篇文章中，我们建议了一个新的瑕疵检测框架，名字为defectNet，它将一个图像分类的结构插入到目前（state-of-the-art）的目标检测框架中，以便一次性的实现对是否包含瑕疵进行判决和对瑕疵对象进行物体检测。首先，它先对图像进行分类，根据分类的结果再决定是否再对图像进行物体检测。图？（c）展示了我们的检测模型。~~实验结果表明我们的defectNet对瑕疵的检验能力（acc）比Faster R-CNN高出了？%，比SSD高出了？%，mAP比SSD高出了%，但是和Faster R-CNN几乎一样，速度和Faster R-CNN和SSD保持一致，我们的defectNet acc比直接进行图像分类低了？%，但是速度比它快了？倍。除此之外，我们还建议了一个新的生成先验框的方法，该方法~~。我们的方法的目的不是为了取代和超越现今的物体检测框架，而是为了弥补它们在某些细分的物体检测领域方面的不足。我们的贡献也许很微小，但是它促进了深度卷积网络在目标检测领域更加系统和完善。

我们总结我们的贡献如下：

我们建议了一个defectNet，一个瑕疵检测框架，该框架能够插入到现有的物体检测框架中，并且它对瑕疵的检验能力超过了现有物体检测方法，弥补了他们在瑕疵检测领域方面的不完美；

我们在Fabric Detects Dataset对我们的模型进行了实验和分析，并且和现今的物体检测框架做了比较。实验结果表明我们的框架具有较强的实用性。

# DefectNet

现今基于CNN的主流的目标检测框架主要分为两种，一种是基于区域推荐的，即先用传统的图像算法或者训练一个CNN生成候选建议框，然后再用CNN进行目标的分类和候选框的回归，另一种是使用单个CNN直接实现目标的分类和锚点的回归。图2（a）和(b)分别展示了这两种结构。然而，在实际的瑕疵检测中，不含瑕疵的图像应该比含有瑕疵的图像要多得多，如果采用（a）和(b)这两种结构，它们的计算量应该会比先进行瑕疵判决再进行瑕疵检测的计算量要多，因此本文提出了defectNet，图2（c）展示了这种结构，它由backbone网络、Defect image分类、head、Box回归、Box分类组成。

## Backbone

The backbone network is mainly used to extract image features for object classification and location in the object detection frameworks, there are a number of excellent networks for image classification so far, such as VGGNet, GoogleNet, ResNet, DenseNet and so on. In this paper, we select ResNet-50 as our backbone network for the efficiency and accuracy. Figure 3 illustrates the ResNet-50 network that consists of an input head, four sequential stages and the final output layer. The input head includes a 77 convolution kernel with an output channel of 64 and a stride of 2, a max pooling layer with a stride of 2. After an image passes through the input head, its width and height decreases by 4 times and its channels size increases to 64.

Each stage of ResNet-50 starts with a downsampling block and followed by several residual blocks. In the downsampling block, there are two paths, namely path A and path B. Path A is the main path, where includes three convolutions, we call them conv1, conv2 and conv3, their kernels size is 11, 33, 11 respectively. Instead, path B has only a 11 convolution, which is called conv4. Path B is also called shortcut connection. The conv1 and conv2 have the same output channels, but the output channels of conv3 are four times as many as those of conv1 and conv2. In order to sum outputs of both paths, conv4 has the same output channels with conv3. A residual block is similar to the downsampling block except without conv4 in path B and only using convolutions with a stride of 1. In stage 1, the strides of all convolutions are 1, which make the input width and height remain unchanged. Starting from stage 2, the strides of conv2 and conv4 are 2 to halve the input width and height. The downsampling block together with residual block are named as bottleneck, stage 1, stage 2, stage 3, stage4 of ResNet-50 have 3, 4, 6, 3 bottlenecks respectively. The final output layer is an average pooling layer and a full connection layer. There are many different residual network models by setting the different number of residual blocks in each stage, such as ResNet-101, ResNet-152, where the number represents the number of layers in the network.

## Defect Judgement

在几乎所有的目标检测框架中，往往只需要提取backbone中前面几层的特征图信息，而最后的输出层往往丢弃。在本文中，我们重新提取最后的输出层信息，因为它能够帮助我们对图像是否包含瑕疵进行判决。输入图像经过backbone的卷积操作后，最后只剩下高级的语义信息，我们对最后一层特征图进行平均池化操作，然后展开成一维向量，在经过两个全连接操作，最后经过Soft Max层，从而输出是否包含有瑕疵的判决信息。

我们引入binary cross entropy loss 给图像瑕疵分类，定义如下：

where X是输入的图像，y（0，1）是图像的标签，0表示没有瑕疵，1表示有瑕疵，p表示包含瑕疵的概率。

## Features Pyramid Network

For the classification problems, we usually need deeper semantic information, while for location, the semantic information in the shallow layers is more important. The feature pyramid network adopts a lateral connection of feature maps to have both of these characteristics. Hence, we use FPN as our head. Figure 1(a) describes the construction of the feature pyramid networks. The structure of feature pyramid networks involves a bottom-up pathway, a top-down pathway and corresponding lateral connections. The bottom-up pathway is the feed-forward computation of the backbone, where feature maps are selected from the output of the last layer of each stage in the backbone network. The selected feature maps have the different number of channels and their width and height are halved in sequence. Through upsampling spatially coarser, the top-down pathway generates higher resolution feature maps by two times, whose semantic information is stronger but localized information is weaker. The lateral connections between the top-down pathway and the bottom-up pathway settle the matter, which enhance the localized information of feature maps in the top-down pathway by merging feature maps of the same spatial size from the bottom-up pathway and the top-down pathway and make more accurate predictions.

## Bounding Box Regression and Classification

A bounding box 这里介绍候选框回归息。

## Loss Function

我们的损失函数由三部分组成：瑕疵图像分类的损失，物体检测对象的置信度损失和位置损失。

Defect Image Classification Loss

参数alpha意味着瑕疵图像分类损失所占的权重。

# Implementation Details

啊手动阀手动阀阿三发射点发了计算得分萨拉发动机螺丝扣搭街坊

Model

这里介绍实现细节

这里介绍三种结构，（a）直接回归分类、（b）先分类再回归、（c）同时分类和回归的

# Experiments

## Fabric Defects Dataset

In order to verify the efficiency of our models, we introduce a fabric defect dataset which was collected in the real textile workshop. The fabric defect dataset is composed of plain fabrics and patterned fabrics. The plain fabrics have ???? normal images and ???? defect images, the patterned fabrics have ???? normal images and ???? defect images. The number of plain fabrics defects categories and patterned fabrics defects categories is ?? and ?? respectively. Table ? and Table ? shows their name and number of per defects categories severally in detail.

## 实验结果（和(a)、(b)的比较

介绍训练过程，介绍实验结果，分析实验结果。

## Ablation Experiments

# Discussion

为什么要提出瑕疵网络？

为什么瑕疵网络要快？

瑕疵网络

# Related Works

# Conclusions

# Acknowledgment

For the purpose of

Table ? The name and number of per defects categories of plain fabrics

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| |  |  | | --- | --- | | Name | Number | | hole | 1??? | | water stain | 2??? | | oil stain | 3??? | | soiled | 4??? | | three silk | 5??? | | knots | 6 | | card skip | 7 | | mispick | 8 | | card neps | 9 | | coarse end | 10 | | loose warp | 11 | | cracked ends | 12 | | |  |  | | --- | --- | | buttonhole selvage | 13 | | coarse picks | 14 | | looped weft | 15 | | hard size | 16 | | warping knot | 17 | | stitch | 18 | | skips | 19 | | broken spandex | 20 | | thin thick place | 21 | | buckling place | 22 | | color shading | 23??? | | smash | 24 | | roll marks | 25 | | |  |  | | --- | --- | | take marks | 26 | | singeing | 27 | | crinked | 28 | | uneven weaving | 29??? | | double pick | 30??? | | double end | 31??? | | felter | 32??? | | reediness | 33??? | | bad weft yarn | 34??? | |  |  | |  |  | |  |  | |  |  | |

~~从图？中，我们可以看出，布匹疵点数据集的长宽比分布不正常。~~

Append Index

Table ? The name and number of per defects categories of patterned fabrics

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Name | Contamination | Mis-pattern | Watermark | Variegated wool | Sewing | Sewing head seal |  |  |  |  |  |  |  |  |  |
| Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  | | --- | --- | | Name | Number | | stain | 1 | | broken figures | 2 | | water stain | 3 | | variegated wool | 4 | | seam allowance | 5 | | seam allowance marks | 6 | | chongnian | 7 | | |  |  | | --- | --- | | hole | 8 | | pleat | 9 | | knit fault | 10 | | through printing | 11 | | wax spot | 12 | | color shading | 13 | | broken silk | 14 | | others | 15 | |