



Article Title: A Fabric Defect Detection Method Based on Deep Learning

A Fabric Defect Detection Method Based on Deep Learning

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ABSTRACT

Fabric defect detection is a challenging task in the fabric industry because of the complex shapes and large variety of fabric defects. Many methods have been proposed to solve this problem, but their detection speed and accuracy were very low. As a classic deep learning method and end-to-end target detection algorithm, YOLOV4 has evolved rapidly and has been applied in many industries, showing good performance. This paper proposes an improved YOLOv4 algorithm with higher accuracy for fabric defect detection, in which a new SPP structure that uses Soft Pool instead of Max Pool is adopted. The improved YOLOv4 algorithm with three Soft Pools can process the feature map effectively, which has a significant advantage in reducing the negative side effects of the SPP structure and improving the detection accuracy. The improved SPP structure is used by the three outputs of Backbone, and in order to ensure that the output can be inputted into the subsequent PANet successfully, the network structure is improved that a series of convolution layers after the SPP structure is added for reducing the channel numbers of feature map to an appropriate value. In addition, contrast-limited adaptive histogram equalization is adopted in advance to improve the image quality, which results in strong anti-interference abilities and can slightly increase the mAP. Experimental results show that, compared with the original YOLOV4, the improved YOLOV4 increases the mAP effectively by 6%, while the FPS only decreases by 2. The improved YOLOv4 can identify the location of defects accurately and quickly, and can also be applied in other defect detection industries.

Keywords: Fabric Defect Detection, Fabric Industry, Yolov4 Algorithm, Deep Learning, Histogram Equalization, Layers.

1 Introduction

Fabric defect detection is an important step in the fabric production process. Human inspection with eyes for fabric defects is the traditional method used in the fabric industry, and visual inspections can identify and locate the defects. However, the human detection rate only reaches up to 12 meters per minute, and is a monotonous job with high repetition, a wasteful use of human resources and increasing costs, making it unsuitable for use in mass production. Although human detection is simple, the cloth production lines and cloth outputs are becoming more complex, which creates obstacles for workers in correctly identifying the location of defects. Additionally, cloth defects lead to a reduction in cloth prices, resulting in losses of 45%-65% for the cloth manufacturer. Therefore, a new detection method, which has high



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detection accuracy and detection speed, is needed to replace the manual work currently used. With the advent of CNN (convolutional neural networks), and the development of deep learning and machine vision, many detection methods, combining the advantages of deep learning and machine vision, have emerged, replacing traditional manual methods and image processing. In this paper, first, the K-means clustering algorithm is analysed to select the optimal anchor value according to the aims of this paper. Then, the structure of the SPP-net of the original YOLOv4 is analysed, and its disadvantages are summarized. In addition, addressing the disadvantages, an improved YOLOv4 algorithm with improved SPP (Spatial Pyramid Pooling) and CLAHE (contrast-limited adaptive histogram equalization) is proposed. Finally, the improved YOLOv4 is compared with four classic algorithms: YOLOv4 with CLAHE, the original YOLOv4, Faster R-CNN and SSD (Single Shot Multi Box Detector), where the mAP is the main performance evaluation index. In addition, defect images and detection effect images are presented, which have clear contrasts. The anchor of YOLO and SSD learns from Fast R-CNN. The final prediction part of YOLOv4 is carried out in three feature maps, each of which has a grid point with three anchors. YOLO obtains the width and height parameters of the BBox (bounding box) in advance. In the regression prediction phase, only the width and height parameters need to be adjusted instead of rebuilding the BBox. So the setting of good anchor parameters can accelerate the rate of convergence of the network training. The K-means clustering algorithm is used in YOLOv2 to process the Gt BBox (ground truth bounding box). The original K-means clustering generally uses a Euclidian distance to complete the clustering but a large target will result in a large Gt BBox that can lead to a large anchor, which can enlarge the Euclidian distance of a large box. The situation is obviously unreasonable, so the processed IOU is used in YOLOv2 instead of the Euclidian distance. The processed IOU represents the degree of overlap between each cluster center and other boxes. The original IOU indicates that the value of the IOU grows larger as the degree of overlap is higher, but the Euclidian distance that is expected in this paper is smaller when the degree of overlap is higher.

The presence of fabric defect makes the final garment product faulty. It has been reported in that fabric defects cause about 85% of the defects detected in the garment industry. Fabric prices decrease by 45%–65% for second or off quality goods. It is therefore of great importance that these defects are detected, recognized and prevented from reoccurring. There are a large number of types of fabric defects. Among them, color yarn, missing yarn, hole, slub, crease mark and spot are the notable ones, which are shown in Figure 1. The quality of textile products important phase of quality improvement. An automated fabric defect inspection system increase the product quality, which poses improved productivity to conform to customer needs and to lessen the costs associated with quality degradation.

2 Related Works

Ross Girshick, Fast R-CNN [2015] [1]. This paper proposes a Fast Region-based Convolutional Network method (Fast R-CNN) for object detection. Fast R-CNN builds on



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previous work to efficiently classify object proposals using deep convolutional networks. Compared to previous work, Fast R-CNN employs several innovations to improve training and testing speed while also increasing detection accuracy. Fast R-CNN trains the very deep VGG16 network $9\times$ faster than R-CNN, is $213\times$ faster at test-time, and achieves a higher mAP on PASCAL VOC 2012. Compared to SPPnet, Fast R-CNN trains VGG16 $3\times$ faster, tests $10\times$ faster, and is more accurate. Recently, deep ConvNets have significantly improved image classification and object detection accuracy. Compared to image classification, object detection is a more challenging task that requires more complex methods to solve. Due to this complexity, current approaches train models in multi-stage pipelines that are slow and inelegant. Complexity arises because detection requires the accurate localization of objects, creating two primary challenges. First, numerous candidate object locations (often called “proposals”) must be processed. Second, these candidates provide only rough localization that must be refined to achieve precise localization. Solutions to these problems often compromise speed, accuracy, or simplicity. We propose a single-stage training algorithm that jointly learns to classify object proposals and refine their spatial locations.

Kaiming He, Xiangyu Zhang, Deep Residual Learning for Image Recognition [2015] [2]. Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers— $8\times$ deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. Deep convolutional neural networks have led to a series of breakthroughs for image classification. Deep networks naturally integrate low/mid/high level features and classifiers in an end-to-end multilayer fashion, and the “levels” of features can be enriched by the number of stacked layers. Recent evidence reveals that network depth is of crucial importance, and the leading results on the challenging ImageNet dataset all exploit “very deep” models, with a depth of sixteen to thirty. Many other nontrivial visual recognition tasks have also greatly benefited from very deep models. Driven by the significance of depth, a question arises: An obstacle to answering this question was the notorious problem of vanishing/exploding gradients, which hamper convergence from the beginning. This problem has been largely addressed by normalized initialization and intermediate normalization layers, which enable networks with tens of layers to start converging for stochastic gradient descent (SGD) with back propagation.

Chien-Yao Wang, Hong-Yuan Mark Liao, CSPNET: A New Backbone That Can Enhance Learning Capability Of CNN [2019] [3]. In this paper, we propose Cross Stage Partial Network (CSPNet) to mitigate the problem that previous works require heavy inference computations from the network architecture perspective. Neural networks have enabled state-



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of-the-art approaches to achieve incredible results on computer vision tasks such as object detection. However, such success greatly relies on costly computation resources, which hinders people with cheap devices from appreciating the advanced technology. We attribute the problem to the duplicate gradient information within network optimization. The proposed networks respect the variability of the gradients by integrating feature maps from the beginning and the end of a network stage, which, in our experiments, reduces computations by 20% with equivalent or even superior accuracy on the ImageNet dataset, and significantly outperforms state-of-the-art approaches in terms of AP50 on the MS COCO object detection dataset. Neural networks have been shown to be especially powerful when it gets deeper and wider. However, extending the architecture of neural networks usually brings up a lot more computations, which makes computationally heavy tasks such as object detection unaffordable for most people. Light-weight computing has gradually received stronger attention since real-world applications usually require short inference time on small devices, which poses a serious challenge for computer vision algorithms. Although some approaches were designed exclusively for mobile CPU, the depth-wise separable convolution techniques they adopted are not compatible with industrial IC design such as Application-Specific Integrated Circuit (ASIC) for edge-computing systems.

Joseph Redmon, Santosh Divvala, You Only Look Once: Unified, Real-Time Object Detection [2016] [4]. We present YOLO, a new approach to object detection. Prior work on object detection repurposes classifiers to perform detection. Instead, we frame object detection as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimized end-to-end directly on detection performance. Our unified architecture is extremely fast. Our base YOLO model processes images in real-time at 45 frames per second. A smaller version of the network, Fast YOLO, processes an astounding 155 frames per second while still achieving double the mAP of other real-time detectors. Compared to state-of-the-art detection systems, YOLO makes more localization errors but is less likely to predict false positives on background. Finally, YOLO learns very general representations of objects. It outperforms other detection methods, including DPM and R-CNN, when generalizing from natural images to other domains like artwork. Humans glance at an image and instantly know what objects are in the image, where they are, and how they interact. The human visual system is fast and accurate, allowing us to perform complex tasks like driving with little conscious thought. Fast, accurate algorithms for object detection would allow computers to drive cars without specialized sensors, enable assistive devices to convey real-time scene information to human users, and unlock the potential for general purpose, responsive robotic systems. Current detection systems repurpose classifiers to perform detection.

Kubilay Tuna, Levent Seyfi, Faults Detection with Image Processing Methods in Textile Sector [2018] [5]. In this study, 5 MP Raspberry Pi camera modules is used to detect the image of the fabric moving through the conveyor band and a Raspberry Pi 3 minicomputer to process



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the received image and display it on the touch screen. The quality control process for determining fabric faults causes high cost and time loss when performed with human eyes. Adding a real-time system to the fabric production mechanisms is very difficult to detect mistakes. In addition, studies on the inspection of the faults in the woven fabrics, which are the most applied areas of image processing methods, have been investigated and thresholding method, HSV color space transformation and morphological processes have been used in order to detect the fault in any fabric accurately and correctly. The most suitable threshold values for these methods have been determined by testing in the images obtained as a result of the investigations. The quality and smoothness of fabric surfaces is of great importance in the textile industry. The demand for fabrics, which are very common in use, has increased rapidly, especially with the continuous growth in fashion sector. Parallel to the increase in demand, fabric production also increases at the same rate. Only the quality of the fabrics produced should not fall. If the production of defective products due to faults found in fabrics is realized, the producers may suffer serious material damage. For this reason, the fabrics to be produced must be checked before they are offered to consumers. Inspection of fabric surfaces in the production is very beneficial in terms of production cost because the fastest and most accurate job is done. If this observation is done based on the human eye, production slows down and it is insufficient to examine the types of errors that are difficult to detect.

Kazim Yildiza, Ali Buldu, A novel thermal-based fabric defect detection technique [2015] [6]. In this paper, a new method based on the use of thermal camera for detecting these defects from the textile fabric images is presented. For identification process of defective area, fabric images were obtained by a thermal camera during the fabric flow in quality control machine that was specially designed for this experiment. During the fabric production process, many defects can be occurred stemming from the unevenness in spinning, weaving, finishing processes, or from the raw materials. The fabric quality control process for the detection of these defects is carried out by specialist operators. Defective and defect-free regions on fabric surface were determined by thermal camera due to the thermal differences. The mentioned thermal defect detection system will eliminate the worker usage for fabric quality control process, thus it will provide a cost-effective and competitive manufacturing. In textile industry, during the production of fabrics from raw materials (yarn, fiber, etc.), many errors have been encountered from the weaving and finishing processes. The fabric quality control process for the detection of these errors is carried out by specialist operators. This process is made by quality control personnel by using illuminated, oblique quality control boards. While fabric is passed over the illuminated surface of the quality control desk, defective regions are scanned with eye and are determined by quality control personnel. Its accuracy depends on quality control operator's attention and experience. The experimental results proved that human eyesight is limited and this system can recognize just 50–70% of the fabric defects.



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3 Proposed Work

The proposed scheme is an improved YOLOv4 algorithm with higher accuracy for fabric defect detection, in which a new SPP structure that uses Soft Pool instead of MaxPool is adopted. The improved YOLOv4 algorithm with three Soft Pools can process the feature map effectively, which has a significant advantage in reducing the negative side effects of the SPP structure and improving the detection accuracy. The improved SPP structure is used by the three outputs of Backbone, and in order to ensure that the output can be inputted into the subsequent PANet successfully, the network structure is improved that a series of convolution layers after the SPP structure is added for reducing the channel numbers of feature map to an appropriate value. In addition, contrast-limited adaptive histogram equalization is adopted in advance to improve the image quality, which results in strong anti-interference abilities and can slightly increase the mAP.

The main objective proposed in this project has been improved for small cloth defect areas that are close to the background shape, and has overcome the low efficiency of the traditional manual detections. The improved YOLOv4 proposed in this project can be extended to other surface defect detection fields, among which batch detection of wood surface defects is one example. The model proposed in this project has high precision and excellent real-time performance, and can be effectively applied for defect detections in industrial fabrics.

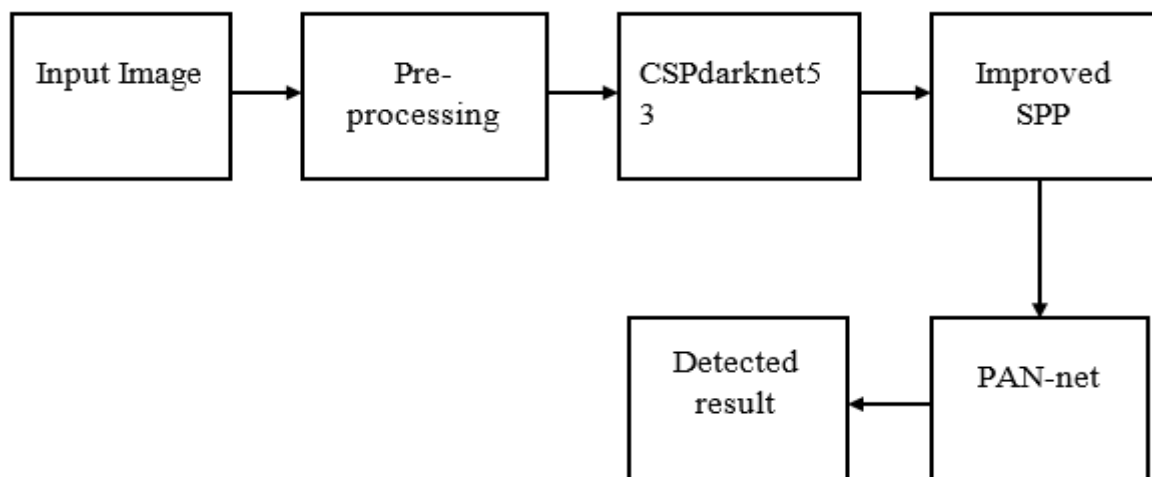


Figure 1: *Proposed Architecture design*

3.1 A Modules

Pre-processing: CLAHE is an enhanced version of HE (histogram equalization), which is a simple and effective image enhancement method and can increase the contrast of images by adjusting the image's gray distribution. If the pixel value of the original image is relatively concentrated in the gray histogram, HE can increase the range of gray differences between pixels to obtain a clearer image.



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CSPdarknet53: The backbone network part of Yolov4 applies the CSPDarknet5. The CSPDarknet53 network is a CSPNet (Cross Stage Partial Network) network added on the basis of Darknet53. Darknet53 draws on the idea of ResNet, namely residual connection, to ensure that the network has depth while also alleviate the vanishing gradient problem. CSPNet can enhance the learning ability of CNN, while reducing the amount of calculation and memory cost.

Improved SPP: The improved SPP uses Softpool that selects the feature map in proportion to the corresponding value of the element, which avoids the advantage of Maxpool that misses some details. In addition, the improved SPP is adopted after the three feature maps are output by the backbone. The improved YOLOv4 adopts the improved SPP based on softmax, and three convolutions are added to the upper and middle of the improved SPP that uses gradient information to improve the training effect, which increases the computation speed and reduces the running memory.

PAN-net: The modified Path Aggregation Network (PANet) starts with a bottom up path propagating feature maps from scale three up to the first scale. This path enhances the localization capability of the entire feature hierarchy. By propagating low level patterns such as edges or instance parts through the scales, large instances can be accurately localized and identified. Higher resolution feature maps respond strongly to entire objects while lower ones focus more on lowlevel patterns. That is why PANet implements a top down path to propagate semantically strong features and enhance all lower resolution features.

YOLOV4 Algorithm: The YOLOv4 algorithm is a single-stage object detection algorithm that divides the image into a grid of cells and predicts bounding boxes and class probabilities for each cell.

4 Result and Discussion

The deep learning framework adopted in this paper is PyTorch 1.2 based on the Windows 10 platform. The computer configuration for this experiment is as follows: CPU: Inter Xeon W-2245 with 3.90 GHz, GPU: NVIDIA Quadro P4000, video memory: 8 GB, RAM: 64 GB, SSD: 512G. The programming language is Python3.6, and Open CV is adopted for image processing. The parameters of image size of the backbone, the learning rate and the decay rate are set to 416×416 , 0.001 and 0.93, respectively. A learning rate of 0.93 indicates that the learning rate of each epoch becomes 0.93 times that of the previous epoch. One thousand epochs are trained, and the network trains the NECK part for 500 epochs by freezing, and the backbone epochs by unfreezing. The setting for the parameter batch size has been adjusted several times based on the theory that the optimal batch size is between 2 and 32. Batch size is set to 16 before freezing and then reset to 4 in consideration of the computer configuration after thawing. The improved SPP architecture requires testing to measure its improvement; some of the tricks, such as mosaic data augmentation and cosine dependency schedulers, run well sometime and are sometime unstable. After a thousand iterations, the loss value fluctuates by approximately 0.4, which proves that the model proposed in this paper has good performance and has converged.



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The detection results for fabric defects are displayed by the index mAP in the VOC dataset to evaluate the accuracy of the model; the visualization of each detection box is not evaluated. Two indices, precision and recall, are often used to evaluate the performance of target detection models, before which they are adopted, and the threshold value of IOU should be preset. When the degree of overlap between the prediction box and the real box is greater than the threshold value of IOU, the corresponding sample is called a positive sample; alternatively, the corresponding sample is called a negative sample.

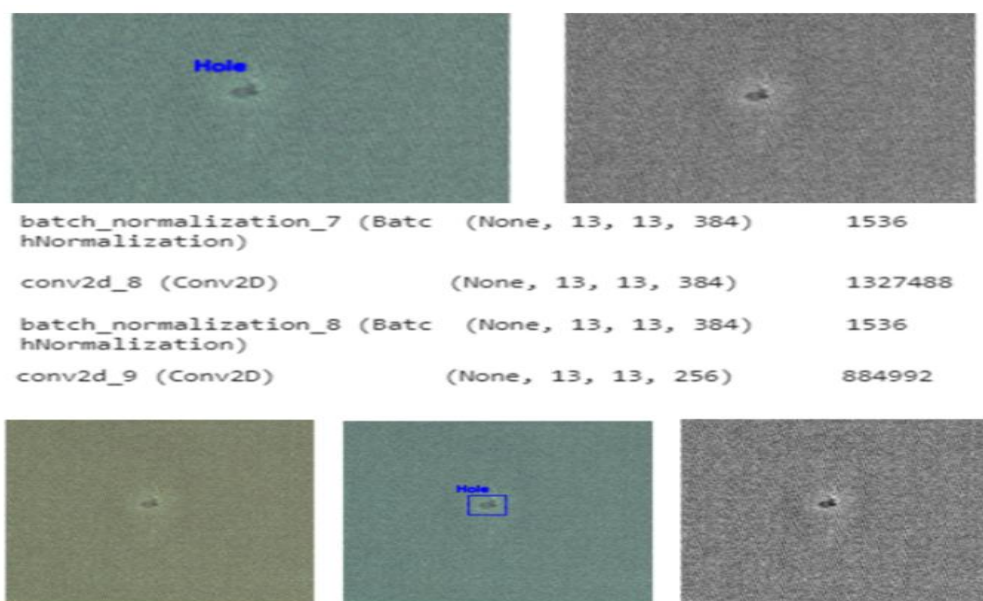


Figure 2: Detected Fabric Defect

5 Conclusion

The model proposed in this project has been improved for small cloth defect areas that are close to the background shape, and has overcome the low efficiency of the traditional manual detections. Compared with the original YOLOv4, the improved YOLOv4 upgrades mAP by 6%, while FPS only decreases 2. Based on extensive research and a detailed analysis of fabric defects, our network model is the most suitable for fabric defect detection. Therefore, the improved YOLOv4 proposed in this project can be extended to other surface defect detection fields, among which batch detection of wood surface defects is one example. The model proposed in this project has high precision and excellent real-time performance, and can be effectively applied for defect detections in industrial fabrics.

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