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SSD-BASED CARTON PACKAGING QUALITY DEFECT DETECTION SYSTEM FOR THE LOGISTICS SUPPLY CHAIN

Abstract: With the deepening of green and sustainable development and the rapid development of the social economy, the modern logistics industry has also developed to an unprecedented level. In the logistics supply chain, due to the high value of the items inside the arrival carton, appearance inspection must be carried out before warehousing. However, manual inspection is slow and ineffective, resulting in the waste of manpower and packaging carton resources, which is not conducive to sustainable development. To address the above problems, this paper designs a logistics supply chain carton packaging quality defect detection system based on improved Single Shot MultiBox Detector (SSD) in the context of green sustainable development. The Implicit Feature Pyramid Network (IFPN) is introduced into SSD to improve the feature extraction ability of the model; the multiscale attention mechanism is introduced to collect more feature information. The experiment shows that the mAP and FPS of the system on the self-built data set reach 0.9662 and 36 respectively, which can realise the detection of the appearance defects of logistics cartons and help promote green sustainable development.

Keywords: green and sustainable development, logistics supply chain, SSD, implicit Feature Pyramid Network, multiscale attention mechanism

Introduction

Green and sustainable development is a new development mode based on the constraints of ecological environmental capacity and resource carrying capacity, considering environmental protection and economic [1]. With the implementation of a sustainable strategy and the development of the modern economy, the circulation of goods has broken the geographical limitation to a great extent, and the regional span is much wider than in any previous era. Logistics carton is a kind of paper packaging, and because of high-cost performance is widely used. However, in the logistics and transportation process, cartons still produce breakage and deformation problems and are easily contaminated by painting and oil stains [2]. Therefore, studying an efficient quality inspection model for carton packaging can help logistics enterprises find various defects in carton packaging in time, reduce human and material resources, and help green sustainable development.

With the rapid development of artificial intelligence technology and computer computing power, target detection models are widely used in the field of packaging defect

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detection for various items. Earlier, the implementation of target detection models was mostly based on the time-consuming and labour-intensive traditional method of manual feature extraction. First, the region of interest is obtained by using window sliding on the image to be detected; second, feature extraction is performed on the sliding window using algorithms such as Scale Invariant Feature Transform (SIFT), Histogram of Oriented Gradient (HOG), and Speeded Up Robust Features (SURF) [3] based on hand-designed features; then, feature classification is performed using classifiers such as Support Vector Machine (SVM) and AdaBoost [4]; finally, whether the window contains a certain type of target of interest is detected. These methods are deficient due to their reliance on manual features with weak scalability, which leads to difficulties in extracting effective features in the face of complex categories and environments [5].

In this paper, we focus on logistics carton packaging quality defect detection in the context of green and sustainable development and propose an improved SSD based carton packaging quality defect detection system for the logistics supply chain. Firstly, IFPN is deeply fused with the SSD detection framework to extract better quality features while reducing the computational complexity of the SSD network; meanwhile, multiscale attention mechanism is added to the convolution layer to fuse feature maps with different scales to obtain more detailed features.

Related work

Packaging affects the quality and reputation of products, as well as the green and sustainable development of the company, so the quality detection of packaging is particularly important. Due to the development of computer image processing technology and deep learning methods, research scholars and corporate researchers have conducted extensive research on the quality defect detection of various product packaging using target detection algorithms in deep learning and obtained corresponding scientific results, which effectively promote the green and sustainable development of various industries [6]. The object detection algorithm aims to find the position of the object in the given image and mark the object category. According to the different detection ideas, target detection algorithms can be divided into candidate region based algorithms [6, 7] and boundary regression based algorithms [8, 9]. Among them, the candidate region based algorithm divided regions containing targets, so the neural network can learn a lot of useful information and thus achieve good detection accuracy. However, generating target candidate regions requires many time and computational resources, which cannot meet the requirements of detection. To compensate for the time consumption, the boundary regression based algorithm directly used convolutional networks to extract features from images and locate targets for classification. Although the above work has made significant progress, it still performs poorly in target scale diversity and detection of small and dense targets.

YOLOV3 algorithm solves the problem of redundant channels when channel attention is used to concatenate features of different scales. At the same time, spatial attention mechanism is used to obtain the location distribution of input features in spatial dimensions, so as to retain effective information in the detection process. To achieve higher mAP, Lin et al added a top-down path to the backbone network for feature extraction to address the problem of target scale variation [10]. Singh and Davis proposed a SNIP based on the image pyramid structure to reduce the effect of scale variation during training [11].

PANet used ROI alignment for each layer of the pyramid features and then takes the maximum value for fusion to extract more features [12]. NAS-FPN used neural architecture search to select the best model, to improve the detection performance of FPN [13]. FSSD used feature information from different scales for detection to enhance the detection ability of small targets [14].

Improved SSD-based carton packaging quality defect detection system for logistics supply chain

The appearance of the logistics carton must be checked before storage. First select the delivery supplier, select the goods to be delivered, click to start detection. The industrial camera captures the appearance image of the carton, and the system detects whether there are defects. At the same time, start the alarm, to be checked manually, to determine the continued storage or return. And the corresponding number of defective boxes are accumulated. After the detection is complete, the results are stored in the database for query calls. In order to realise the functions of detection, information processing and query, the system proposed in this paper is mainly divided into three modules, namely, the logistics carton appearance defect detection module, the manual verification information processing module and the query module. The appearance defect detection module of logistics carton is used to realise the automatic identification of appearance defects of logistics carton and achieve accurate detection according to the requirements of enterprises. After defects are detected, the manual verification information processing module verifies the detected defects and accumulates the number of corresponding defect boxes. After the test, store the test result to the database. The query module is used to realise the query summary of supplier level, item level and defect category level within the selected date.

The query subsystem mainly includes the query of test result information, including the supplier level, the item level and the defect category level. The information processing subsystem is mainly used to manually check the defective cartons, determine the continued storage or return processing, and accumulate the corresponding number of defective cartons, the end of the detection, and store the detection results. The query subsystem is mainly used to realise the summary query of each defect type within the selected date and provide the basis for the reverse analysis of product quality.

Improved SSD carton packaging quality defect detection model

The improved SSD carton packaging quality defect detection model in this paper uses VGG16 as the backbone network to predict the confidence, category, and location information of the carton at each location by convolution of size 3×3 on each feature layer. Eight downsampling operations are implemented on the prediction layer of size Conv4_3, and each subsequent feature prediction layer is half the size of the previous layer. The Implicit Feature Pyramid Network is inserted into the convolutional layer in VGG16 to improve the model's ability to extract features; three multiscale attention mechanisms are incorporated into the Conc7, Conv8_2, and Conv9_2 feature layers of SSD to collect more Contextual feature information.

Implicit Feature Pyramid Network

Feature pyramid network (FPN) can connect different proportion of features through different paths, help the model extract more detailed features, and improve the detection accuracy [15].

The definition of FPN is shown in equation:

$$P = (f_\theta^0 f_\theta^1 \ldots f_\theta^T)(B) \tag{1}$$

where B is the multiscale feature of the network, f_θ^T is the t-th cross-scale connected block, and P is the output of the explicit FPN after fusion of the extracted features.

Although FPN can improve the detection accuracy of the model for cartons, FPN is a layer-by-layer feature fusion mechanism, which only simply stacks multi-scale connected blocks by layer to get a larger sensory field, and the network structure is complex, too much sacrificing the detection speed [16]. In this paper, we propose an Implicit Feature Pyramid Network (IFPN) based on the explicit FPN with the help of the idea of a deep balance model, which reduces the parameter burden and memory loss of the algorithm.

When the number of connected blocks across scales in IFPN is stacked to a certain number, the output will be infinitely close to a point that satisfies.

$$P^* = F_\theta(P^*; B) \tag{2}$$

F_θ is a nonlinear transformation, P^* is IFPN.

Multiscale attention mechanism

In the SSD model for quality defect detection of carton packaging, the problem of semantic divide easily existed due to the different sizes of cartons. In this paper, multiscale attention mechanisms are designed to address this problem. The multiscale attention mechanism fully collects the multi-scale information and context information of the feature map. The three multiscale attention mechanisms proposed in this paper are all U-shaped structures. After the input features go through the multiscale attention mechanism, the output features are spliced with the features of other layers, and then, the 3×3 convolution is used for dimensionality reduction, and the reduced features are subjected to batch normalisation and ReLU activation operation. After that, 3×3 convolution is used again for optimisation. And because the three multiscale attention mechanisms are at different levels and the input features are of different sizes, the downsampling in the multiscale attention mechanism is set to different sizes.

Experiment

In this paper, the experimental environment is Windows 10, the processor is Intel i7-10875H, the memory is 16 GB, and the graphics card is NVIDIA GeForce RTX 2070 with TensorFlow2.3,cuda10.2.

To effectively apply the proposed model to carton packaging quality defect detection, a dataset containing 2000 photos of logistics cartons was collected to train and optimise the model. The mean Average Precision (mAP) and Frames Per Second (FPS) are used to evaluate the detection accuracy and detection speed of the model.

Effect of different IOU thresholds on the detection effect

IOU is an important parameter in target detection. Generally, if the IOU threshold between the detection result and the labelled result is greater than 0.5, the detection result is considered correct; otherwise, the target will be considered undetectable; if the IOU threshold is less than 0.6, the algorithm will be less sensitive to the change of the IOU threshold. When the IOU threshold is larger than 0.6, the model will be greatly affected and its mAP will drop rapidly. To verify the impact of different IOU thresholds on the detection results in this paper's model, training was performed on the publicly available dataset VOC 2007 and the mAP of SSD and this paper's model were compared at IOU thresholds of 0.3-0.7 to determine a more appropriate IOU threshold. The detection results of the two models at different IOU thresholds are shown in Table 1.

Table 1

Comparison of detection effects of different IOU threshold algorithms

IOU threshold	Model	mAP
0.7	Ours	0.7454
	SSD	0.6976
0.6	Ours	0.7577
	SSD	0.7114
0.5	Ours	0.7904
	SSD	0.7465
0.4	Ours	0.7962
	SSD	0.7541
0.3	Ours	0.7962
	SSD	0.7541

When the threshold of this paper's model is 0.4, the mAP is 0.58 % higher than that at a threshold of 0.5, while when the threshold of SSD is 0.4, the mAP is about 0.76 % higher than that at a threshold of 0.5. This is because in the process of detection, various targets will be limited by the environment they are in, so when performing detection, people will focus more on the detection speed and do not require high positional accuracy. Therefore, the IOU threshold was chosen to be 0.4 in the subsequent experiments.

Comparison results of different detection models

SSD, MobileNetV2-SSD, SPP+SSD, FPN+SSD, and the model proposed in this paper were compared in terms of mAP and FPS. The comparison results of the five models are shown in Table 2.

Table 2

Comparison results of five different detection models

Model name	mAP	FPS
SSD	0.8754	8
MobileNetV2-SSD	0.8386	35
SPP+SSD	0.8563	32
FPN+SSD	0.8621	30
Ours	0.9662	36

The proposed model in this paper performs better than SSD, MobileNetV2-SSD, SPP+SSD, and FPN+SSD in terms of FPS. This is because the IFPN proposed in this paper

greatly reduces the complexity and computational loss of the network. In terms of mAP, the algorithm in this paper also achieves optimal results compared to these four algorithms. This is because the multiscale attention mechanism proposed in this paper effectively integrates the feature layers at different scales and extracts more feature information from the images. Therefore, the model in this paper can better achieve real-time accurate carton quality defect detection.

Ablation experiment

To verify the improvement effect of IFPN on FPN, comparative experiments on the accuracy of the detection box are conducted for MobileNetV2 SSD, SPP+SSD and the model in this paper with FPN added. The comparison results are shown in Table 3.

Table 3

Comparison results of detection box accuracy

Carton size	Check box precision		
	MobilenetV2-SSD	SPP+SSD	Ours
Small	0.603	0.632	0.692
Medium	0.551	0.564	0.597
Large	0.913	0.934	0.942

Compared with the other two models, the model in this paper is the best for the detection of large, medium, and small size cartons. Compared with the original SSD with FPN, the algorithm in this paper improves detection box accuracy by 6.2 % for small size cartons, 4.6 % for medium size cartons, and 2.9 % for large size cartons. The experiment shows that IFPN can improve the detection accuracy of the model for various sizes of cartons.

Conclusion

With the in-depth promotion of green and sustainable development, the modern logistics industry has been developed rapidly. However, in the logistics supply chain, the detection of carton packaging quality has problems such as slow speed, poor effect, and waste of resources, which is not conducive to sustainable economic development. Therefore, this paper constructs a logistics supply chain carton packaging quality defect detection system based on improved SSD in the context of green sustainable development, which helps logistics companies to detect the quality problems of carton packaging in time. Introduce IFPN into SSDs to extract more and better features; the multiscale attention mechanism is added to the convolution layer of the VGG16 network to fuse feature maps with different scales to obtain more detailed carton image features. Experiments show that the system in this paper can effectively detect the defects of carton packaging of various sizes in the logistics supply chain and contribute to the green and sustainable development of the logistics industry.

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