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EfficientNetV2 및 YOLOv5를 사용한 금속 표면 결함 검출 및 분류

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Metal Surface Defect Detection and Classification using EfficientNetV2 and YOLOv5

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요 약

철강 표면 결함의 검출 및 분류는 철강 산업의 제품 품질 관리에 중요하다. 그러나 정확도가 낮고 속도가 느리기 때문에 기존 방식은 생산 라인에서 효과적으로 사용할 수 없다. 현재 널리 사용되는 알고리즘(딥러닝 기반)은 정확도 문제가 있으며 아직 개발의 여지가 있다. 본 논문에서는 이미지 분류를 위한 EfficientNetV2와 물체 검출기로 YOLOv5를 결합한 강철 표면 결함 검출 방법을 제안한다. 이 모델의 장점은 훈련 시간이 짧고 정확도가 높다는 것이다. 먼저 EfficientNetV2 모델에 입력되는 이미지는 결함 클래스를 분류하고 결함이 있을 확률을 예측한다. 결함이 있을 확률이 0.3보다 작으면 알고리즘은 결함이 없는 샘플로 인식한다. 그렇지 않으면 샘플이 YOLOv5에 추가로 입력되어 금속 표면의 결함 감지 프로세스를 수행한다. 실험에 따르면 제안된 모델은 NEU 데이터 세트에서 98.3%의 정확도로 우수한 성능을 보였고, 동시에 평균 훈련 속도는 다른 모델보다 단축된 것으로 나타났다.

ABSTRACT

Detection and classification of steel surface defects are critical for product quality control in the steel industry. However, due to its low accuracy and slow speed, the traditional approach cannot be effectively used in a production line. The current, widely used algorithm (based on deep learning) has an accuracy problem, and there are still rooms for development. This paper proposes a method of steel surface defect detection combining EfficientNetV2 for image classification and YOLOv5 as an object detector. Shorter training time and high accuracy are advantages of this model. Firstly, the image input into EfficientNetV2 model classifies defect classes and predicts probability of having defects. If the probability of having a defect is less than 0.25, the algorithm directly recognizes that the sample has no defects. Otherwise, the samples are further input into YOLOv5 to accomplish the defect detection process on the metal surface. Experiments show that proposed model has good performance on the NEU dataset with an accuracy of 98.3%. Simultaneously, the average training speed is shorter than other models.

키워드

Defect Detection, EfficientNetV2, YOLOv5, Classification
결함 검출, EfficientNetV2, YOLOv5, 분류

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I. Introduction

Metal, as one of the primary raw materials for industrial products, will undoubtedly suffer surface damage such as scratches and deformations during processing. The quality and appearance of products will be severely harmed if the metal surface is damaged, so it is critical to detect defects on the metal surface during the manufacturing process. In practice, an inspection of the strips is usually carried out visually by individuals, which is an unreliable and time-consuming procedure. With the advancement of computer vision and pattern recognition, a variety of automated systems for inspecting strip steel have been developed[1,2]. Chengming et al.[3] suggested a back propagation (BP) neural network-based research method for surface quality monitoring of cold-rolled strips. The features were extracted using a wavelet transform, and then images of five different types of typical cold-rolled strip surface defects were studied using the nonlinear properties of a pattern-recognition method based on a BP neural network. The average rate of recognition was 92%. Versaci et al.[4] proposed a fuzzy similarity-based method for developing ultrasonic non-destructive testing and classification technology based on the continuous wave. Yanxi et al.[5] suggested a defect identification technique for strip steel surfaces based on convolutional neural networks (CNN). The automatic extraction and detection of strip steel surface defects were achieved by establishing a CNN model with the introduction of deep learning knowledge and the construction of data sets. Experiments have confirmed the algorithm's efficiency. He et al.[6][7] suggested a hierarchical learning framework based on convolutional neural networks to classify faults in hot-rolled steel, as well as a multi-scale receiving field (MSRF) to be used together with the pretraining model concept-v4 to extract multi-scale features. Simultaneously, several small automated encoders(AE) were trained to adaptively decrease the size of retrieved features to avoid overfitting the training set. Experiments on samples taken from two hot-rolling production lines indicated that the suggested framework reaches classification rates of 97.2% and 97% respectively, which is significantly higher than the traditional method. To deal with various forms of steel surface defects, Lv et al.[8] presented a new end-to-end defect detection network (EDDN). Marco et al.[9] compared the classic machine learning model and the deep learning model in steel defect classification to discuss new methods of steel surface defect identification and classification. Wanget al.[10] proposed a Faster R-CNN method using multilevel features to handle the challenge of detecting different and random defects on the metal plate and strip surfaces.

As mentioned above, with the advancement of machine learning[11] and computer vision, a variety of algorithms have been proposed, and they all have their own strengths and weaknesses. Deep learning-based image classification can only identify photos, but cannot determine the location and magnitude of defects. This has a big impact on the later data analysis. This paper presents a method combining the classification model with the object recognition model. We use the EfficientNetV2[12] model as the backbone of the classification model and object recognition model. By adding CutMix and CutOut data augmentation methods, this model can better detect various shapes of defects, with higher accuracy and better robustness. For object detection we use YOLOv5[13], the most recent version of YOLO[14][32], which is a single, one-shot, end-to-end model that consists of a single convolutional network merged with feature extraction, bounding box prediction, non-maximal suppression, and contextual reasoning. That predicts the bounding boxes as well as their class probabilities.

The organizational structure of this paper is as follows: Section 2 introduces the method of creating of the structure of our algorithm, and the proposed method and overall architecture are presented in section 3. Section 4 analyzes expe- rimental results and compares them with related works. Conclusions are presented in section 5.

II. Methodology

This paper presents a method combining the classification model with the object recognition model.

2.1 Classification model - EfficientNetV2

The EfficientNetV2 is a kind of convolutional neural network that is faster to train and has higher parameter efficiency than earlier models. The authors used a combination of training-aware neural architecture search and scaling to jointly optimize training speed when developing these models. The models are considered in a search space that had been expanded to include new operations like Fused-MBConv. EfficientNetV2 makes extensive use of both MBConv and the newly introduced fused-MBConv in the early layers (Table. 1) and prefers smaller expansion ratios for MBConv, as smaller expansion ratios tend to have memory access overhead.

Table 1. Structure of EfficientNetV2

Stage	Operator	Stride	#Channels	#Layers
0	Conv3x3	2	24	1
1	Fused-MBConv1, k3x3	1	24	2
2	Fused-MBConv4, k3x3	2	48	4
3	Fused-MBConv4, k3x3	2	64	4
4	MBConv4, k3x3, SE0.25	2	128	6
5	MBConv6, k3x3, SE0.25	1	160	9
6	MBConv6, k3x3, SE0.25	2	256	15
7	Conv1x1 & Pooling & FC	-	1280	1

It used smaller 3x3 kernel sizes, but it adds extra layers to compensate for the reduced receptive field resulting from the smaller kernel size. Due to its huge parameter count and memory access overhead, EfficientNetV2 removes the last stride-1 step from the original EfficientNet[15].

2.2 Object detection model - YOLOv5

CNN-based object detectors can be divided into several types: 1) one-stage detectors: YOLOX[16], FCOS[17], Scaled-YOLOv4[18]. 2) two-stage detectors: VFNet[19], CenterNet2[20]. 3) anchor-based detectors: YOLOv5[12]. 4) anchor-freedetectors: CenterNet[21], RepPoints[22]. However, in terms of components, they typically consist of two parts: a CNN-based backbone for image feature extraction, and a detection head for predicting the object's class and bounding box. In addition, object detectors built in recent years frequently insert layers between the backbone and the head, which is commonly called the detector's neck. The main purpose of the Model Backbone is to extract key features from an input image. The Model Neck is used to generate feature-pyramids. Feature pyramids help in the generalization of models on object scaling. It aids in the identification of the same object in various sizes and scales. Feature pyramids are quite useful in assisting models in performing effectively on unknown data. The Model Head is primarily used for the last stage of detection. It creates final output vectors with class probabilities, objectness scores, and bounding boxes by applying anchor boxes on features.

Yolov5[12] (Fig. 1) is based on Yolov1-Yolov4. Yolo is a state-of-the-art, real-time object detector. It has consistently outperformed the competition on two official object detection datasets: Pascal VOC (visual object classes)[23] and Microsoft COCO (common objects in context)[24].

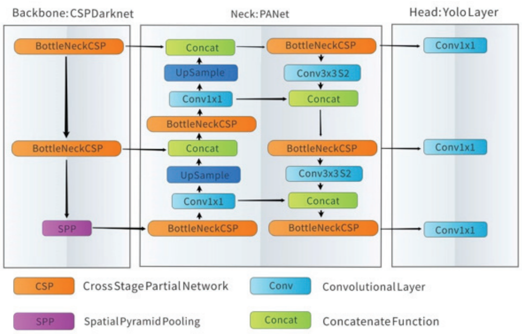

Fig. 1 The network architecture of Yolov5[25]

2.3 Performance evaluations

To accurately evaluate the effect of the model, this paper selects recall, precision, accuracy, mean average precision (mAP), and other metrics to compare the model.

Recall is defined, as in formula (1), which indicates the proportion of positive samples in the sample that are correctly identified.

$$\text{Recall} = TP/(FN+TP) \quad (1)$$

Here, true positive (TP) means that the positive sample is correctly identified as a positive sample and false negative (FN) means that the positive sample is wrongly identified as a negative sample.

The definition of precision is shown in formula (2), which indicates the proportion of real positive samples among the identified positive samples.

$$\text{Precision} = TP/(TP+FP) \quad (2)$$

False positive (FP) means that the negative sample is wrongly identified as a positive sample

Accuracy is generally used to evaluate the global accuracy of a model, which cannot contain too much information and cannot comprehensively evaluate the performance of a model. Its definition is shown in formula (3).

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (3)$$

Here, true negative (TN) means that the negative sample is correctly identified as a negative sample,

Average Precision (AP) is the area under the precision-recall curve. Generally speaking, the better a classifier is, the higher the AP value is. mAP is the average of AP of multiple classes. This means that the AP of each class is averaged again, and the value of mAP is obtained. This metric is the most important one in the target detection algorithm. To do the calculation of AP for object detection, it is necessary to understand Intersection over Union (IoU). The IoU is given by the ratio of the area of intersection and area of union of the predicted bounding box and ground truth bounding box. For mAP@0.5, IoU must be more than 0.5 to be a TP. Another method of calculating AP is AP@IoU = 0.50:0.95 (primary challenge metric). in this method, IoU starts from 0.5 and we increase it to an IoU = 0.95 with steps of 0.05. These will result in computations of AP threshold at ten different IoUs. An average is done to provide a single number which rewards detectors that are better at localisation.

III. The Proposed method

In this work, we need to handle 6 types of defects like scratches (Sc), pitches (Pi), inclusion (In), pitted surface (PS), rolled-in scale (RS), and crazing (Cr). First, Images are classified into with defects or without defects (Fig. 2) through threshold value by EfficientNetV2. EfficientNetV2 classifies 6 types of defects and predicts probability of having defects. And then each prediction is going to be checked by threshold value. If the probability of having a defect less than 0.25, the algorithm directly outputs the sample without defects. Otherwise, images are input into the object detection model YOLOv5. There are three reasons why YOLOv5 is chose as an object detection model. Yolov5 incorporates a Cross-Stage Partial network (CSPNet)[26] into Darknet, resulting in the creation of CSPDarknet as the network's backbone. CSPNet solves the problem of periodic gradient information in large-scale backbones by adding gradient changes into the feature map. It can help in decreasing model parameters and FLOPS (floating-point operations per second), and inference speed and accuracy are increased while simultaneously model size is decreased. Second, to improve information flow, the Yolov5 uses a Path Aggregation Network (PANet) [27] as its neck. PANet uses a new Feature Pyramid Network (FPN) topology with an improved bottom-up path to improve low-level feature propagation. Third, adaptive Feature Pooling, which connects the feature grid to all feature levels, is used to ensure that useful information from each feature level reaches the next subnetwork. PANet improves the use of accurate localization signals in lower layers, which can significantly improve the object's location accuracy. Yolov5, works as an object detector, creating candidate boxes to detect defect spots in images, and it also has image classification module. The final output is the location and classification of the defect in the sample.

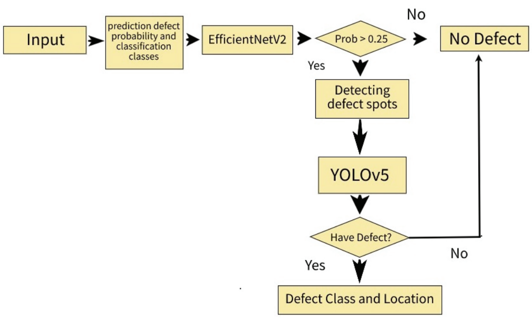

Fig. 2 Flowchart of the proposed model

IV. Experimental Results

For experimental comparisons each method of the network was built up by PyTorch[28] and the experimental platform of this paper uses Windows OS, equipped with CPU Intel® CoreTM i5-9400F @ 2.9GHz, GPU NVIDIA GeForce GTX1060, and 16 GB running memory. NEU dataset[1] was used in this experiment (Fig. 3). It includes six types of common metal surface defects (RS, Pa, Cr, PS, In, Sc). It is difficult to collect the metal surface defect images, so there are only 300 images for each type of defect, a total of 1800 defect images. The image size of the model input is 200 by 200 pixels. The batch size is set to 16, the learning rate is adjusted to 0,01 and it lasts a total of 100 epochs.

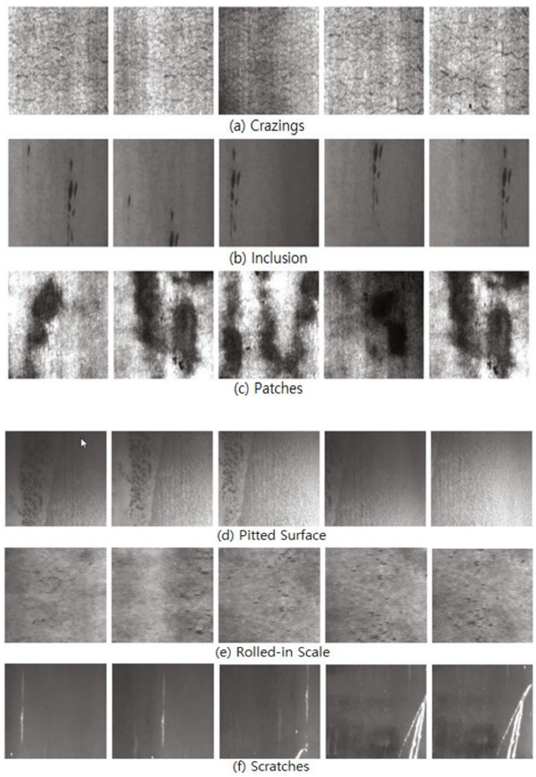

Fig. 3 Six types of metal surface defects

Fig. 4 displays the training and validation loss curves. The loss curve value gradually decreases and tends to converge as the number of iteration times increases. The first one is Box loss curve. Box loss is loss for bounding boxes in object detection. Bounding boxes are used to locate multiple objects in an image. Box loss function gives the error between the predicted and ground truth bounding box. The next is Objectness curve. Objectness loss measures the difference of the predicted “objectness” with the ground truth “objectness”. The existence or absence of an object in an image is defined as objectness. The last one is Classification loss. Classification loss is applied to train EfficientNetV2 for determining the type of defect. It is used to measure the difference between predicted type of defect and actual type of defect.

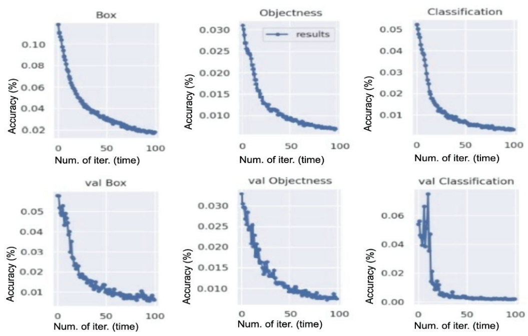

Fig. 4 The curve of loss function

Fig. 5 is the mAP graph. The mAP is comprehensive measurement index commonly used in the field of target detection. It measures the overall detection accuracy of the detection box under different IOUs.

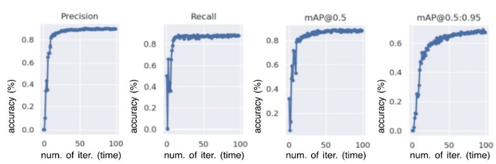

Fig. 5 The curve of the mAP

Using the EfficientNetV2 - YOLOv5 object detection model, detected metal surface defects shown inf Fig. 6.

The proposed model in this work can detect all of the minor defect targets, showing that the proposed model can effectively minimize the chance of missed detection. The detection accuracy of the model in this paper is better than many prior models in detecting the six types of defects.

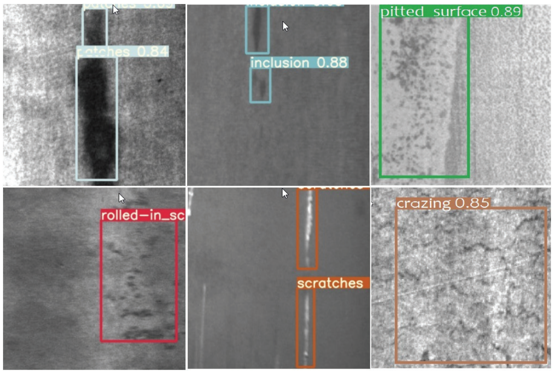

Fig. 6 Detection effect of the algorithm in this paper

As it is shown in the Table 2 “scratch” has the highest average accuracy and “pitted_surface” has the second highest average accuracy with 96.7 %and 94.5 %, respectively. "Rolled-in Scale" has the lowest average accuracy of 81.1%, while the total mean average accuracy is 88.5%.

Proposed model compared with Faster R-CNN, YOLOv3 and SSD models. As it is shown in the Table 2, proposed method has a better result in 5 types of defects than other methods. Besides, model's mAP is 88.3%, indicating that it can accurately detect steel surface defects.

Table 2. The AP of each type of defect and the total mAP of the model

Model	Type of Defect						
	PS	Cr	Sc	Pa	RS	In	mAP
Faster R-CNN[29]	0.845	0.829	0.913	0.916	-	-	0.876
YOLOv3[30]	0.700	0.643	0.749	0.724	-	-	0.704
SSD	0.846	0.421	0.841	0.849	0.631	0.805	0.791
Proposed method	0.945	0.863	0.967	0.845	0.811	0.872	0.883

In general, the suggested method works well in tests on the NEU dataset.

Table 3. Comparison of model accuracy

Model	Accuracy	Time Efficiency ms/image
Wei et al[2]	97%	209.4ms
Improved Faster R-CNN[31]	97.2%	214.5ms
ResNet50 – Faster R-CNN[29]	98%	63.3ms
YOLOv5	96.4%	54.6ms
EfficientNetV2 – YOLOv5	98.3%	57.2ms

In this research, we used a combination of the classification model and the object detection model to increase the algorithm's accuracy and stability while also reducing the average running time of processing each image. As shown in Table 3, EfficientNetV2 – YOLOv5 model's accuracy and time efficiency compared with other models. YOLOv5 has better time efficiency but in terms of accuracy proposed model has better result with 98.3% and also has high time efficiency. Overall, proposed model has better ratio of accuracy and time efficiency and outperformed other lightweight methods.

V. Conclusion

The surface defects of metal are taken as the research object in this paper. The deep learning-based classification network can only classify images, not detect the location and size of defects. In order to achieve automatic detection and localization of metal surface defects, increase the accuracy and stability of the algorithm, and minimize the average running time, we studied a method that fused the EfficientNetV2 binary classification model and YOLOv5 object detection model. By using this model, we can better detect various shapes of defects with higher accuracy and better robustness. Through the square comparison, we demonstrated that this method can be used to detect metal surface defects with high accuracy. The accuracy was 98.3% for the final model. The proposed EfficientNetV2-YOLOv5 can be easily expanded to additional surface defect detection areas in addition to metal surface detection.

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