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Research on Seat Belt Defect Detection Method Based on Deep Learning

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Abstract: *Efficient and accurate methods for identifying and seat belt defects are crucial for the efficient production of seat belts. However, traditional seat belt image recognition and detection algorithms often suffer from issues such as poor adaptability, sensitivity to changes in the working environment.To address this issue, this paper proposes a deep learning based detection model Defeat YOLO, which enhances the spatial semantic information extraction capability of YOLOv10 backbone through CBAM attention mechanism. The improved Defeat YOLO model has significantly improved the accuracy and efficiency of seat belt defect detection.*

Keywords: *Image localization algorithm; Seat belt defects; Deep learning; Defeat-YOLO*

1. Introduction

Seat belts have been widely used in various industries. In the automotive industry, it is used to restrict passengers' body movement in the event of a collision or emergency braking to reduce injuries[1]. With the increase of demand, the supply of seat belts also increases. However, in the production process of seat belts, due to the instability of processing technology, some defects such as scratches, fuzz, weft loss, creases, etc. may occur. These defects not only affect the visual perception and feel, but also pose safety issues during the application process, making quality defect detection after the production of seat belts particularly important [2]. CIS industrial cameras are generally used to scan seat belt samples. Traditional CIS devices[3] rely on image processing algorithms such as edge detection, color space conversion, etc. However, these traditional algorithms suffer from issues such as poor adaptability, sensitivity to changes in the working environment, and unstable performance, leading to missed and false detections. This makes it crucial to enhance their defect detection accuracy to improve detection efficiency.

In the field of industrial defect detection, Jin Lili, Wei Lisheng, and others[4] proposed an improved YOLOv10n network based detection method called AOD-YOLOv10n algorithm to address the problems of slow detection speed, low accuracy, and difficulty in identifying small defects in traditional solar panel surface defect detection methods. Yajun Chen, Yuanyuan Ding, and others[5] summarized the research status of machine learning methods in the key link of surface defect detection in industrial product quality inspection, and analyzed the current application of machine learning methods in surface defect detection. Finally, a comprehensive summary of commonly used industrial surface defect datasets in recent years was provided, providing reference for further research and development of industrial surface defect detection technology. According to the types of data labels[6], learning models can be roughly divided into four categories: fully supervised learning, unsupervised learning, semi supervised learning, and weakly supervised learning. In the category of fully supervised learning models, we can divide the models into two categories based on the input image and the loss function used: representation learning and metric learning. In the category of representation learning, models can be further refined into subcategories such as classification networks, detection networks, and segmentation networks based on their network structure. In short, the classification of models depends not only on whether they require labels, but also on how they process input data and how they optimize their own performance.

Deep learning algorithms improve the accuracy and generalization ability of models by establishing complex neural network models, using large-scale training data, and continuously adjusting their parameters. The YOLO series can provide fast and accurate detection results, and can be trained to adapt to different lighting conditions and background environments, reducing false positives and false negatives. Junwen Chen et al.[7] used deep learning convolutional neural networks to automatically detect defects in fasteners of contact wire support devices. Faiyaz and Md Sabid Hasan[8] used YOLOv8 to detect defects in insulators with high accuracy through comparison and experimentation. These research results highlight the importance of YOLOv8 in enhancing the stability and adaptability of power systems. By achieving rapid and accurate identification of insulator defects in changing outdoor environments, YOLOv8 helps promote monitoring and maintenance of power system infrastructure. This ultimately helps to develop more effective measures to reduce the negative impact of insulator defects on power system performance and stability. In terms of industrial applications, to solve the problems of slow detection speed and low accuracy of surface defects in industrial steel, Li Qiangqiang et al.[9] proposed a detection method based on an improved YOLOv5 network. Add ECANet module to the FPN feature pyramid module of YOLOv5 network to improve detection accuracy; Using the KMeans algorithm to re cluster on the NEU-DET dataset, generating three new sets of prior boxes to reduce network loss; For the small target features of steel defects, ConvNext network is applied to the backbone network of YOLOv5 to extract small target defect features and enhance the model learning ability. The experimental results show that the improved YOLOv5 model has a 3.84% increase in mAP and an average detection rate of 36.9 frame/s compared to the original YOLOv5 model, which can achieve fast and accurate detection and meet practical application requirements. Shuang Mei, Hua Yang et al.[10] proposed a defect detection and localization algorithm that only uses defect free samples for model training. Reconstruct image blocks at different Gaussian pyramid levels using convolutional denoising autoencoder networks, and integrate detection results from different resolution channels to achieve this. The experimental results demonstrate the effectiveness and superiority of this method compared to other methods on surfaces with uniform and irregular textures.

Deep learning technology has played a key role in advancing seat belt defect detection. However, the direct application of deep learning models is difficult to meet the specific requirements of seatbelt defect detection. To address this issue, this article integrates the CBAM attention mechanism into the YOLOv 10 model to enhance its ability to extract various defects in seat belts, thereby improving localization and recognition performance. The improved model, called Defeat YOLO, was trained and tested on a real-world dataset of seatbelt defects. Compared with the original YOLOv 10 algorithm, the improved model achieves 96.6% mAP, which can fully meet the requirements of defect detection. Improved detection accuracy, flexibility, and universality while enhancing feature representation capabilities and reducing other redundant calculations. In summary, introducing CBAM into YOLOv10 can improve the detection performance of the model while maintaining computational efficiency, especially in terms of accuracy and the ability to detect small targets.

2. Methods

2.1 The overview of YOLOv10

YOLOv10 is a new real-time object detection method introduced by researchers from Tsinghua University based on the Ultralytics Python package. It addresses the shortcomings of previous YOLO versions in post-processing and model architecture, as shown in Figure 1, which is a classic architecture diagram of YOLOv10. YOLOv10[4, 11] achieves state-of-the-art performance while significantly reducing computational overhead by eliminating Non Maximum Suppression (NMS) and optimizing various model components. One major highlight of YOLOv10 is its lack of NMS training. Traditional YOLO models use NMS to filter out overlapping predictions, which increases inference latency. YOLOv10 introduces a dual allocation strategy that eliminates the need for NMS, thereby achieving faster and more efficient object detection. The dual allocation strategy includes one to many allocation and one-to-one allocation. One to many allocation is used during the training process to provide rich supervision signals, while one-to-one allocation is used during the inference process to avoid redundant predictions. By using consistent matching metrics to coordinate these two strategies, YOLOv10 achieves high efficiency without sacrificing performance. YOLOv10 adopts a comprehensive model design approach, first adding a lightweight classification head[12]. By using depthwise separable convolution, the computational cost of the classification head is reduced without significantly affecting performance. Secondly, spatial channel decoupling downsampling is adopted to separate spatial reduction and channel addition operations, enhance downsampling efficiency, and reduce information loss. Finally, rank guided block design is carried out to adjust the complexity of the building blocks based on the inherent redundancy at different stages of the model, ensuring optimal utilization of parameters. To further improve accuracy, YOLOv10 integrates large kernel convolution and partial self attention (PSA) modules[13]. Large kernel convolution is selectively used in deeper stages to expand the receptive field without significantly increasing I/O overhead. Another PSA module introduces self attention in a cost-effective manner to enhance the model's ability to learn global representations. These components enhance the model's ability

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to capture global information while maintaining computational efficiency.

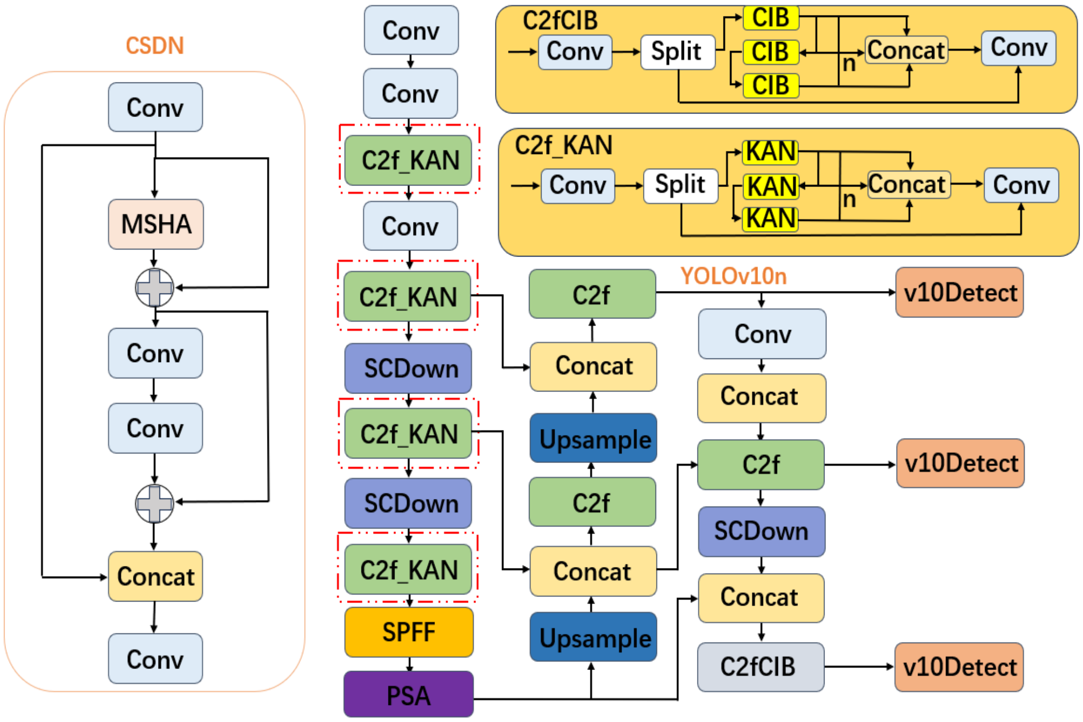

Figure 1: The structure of YOLOv10

2.2 Convolutional Block Attention Module (CBAM)

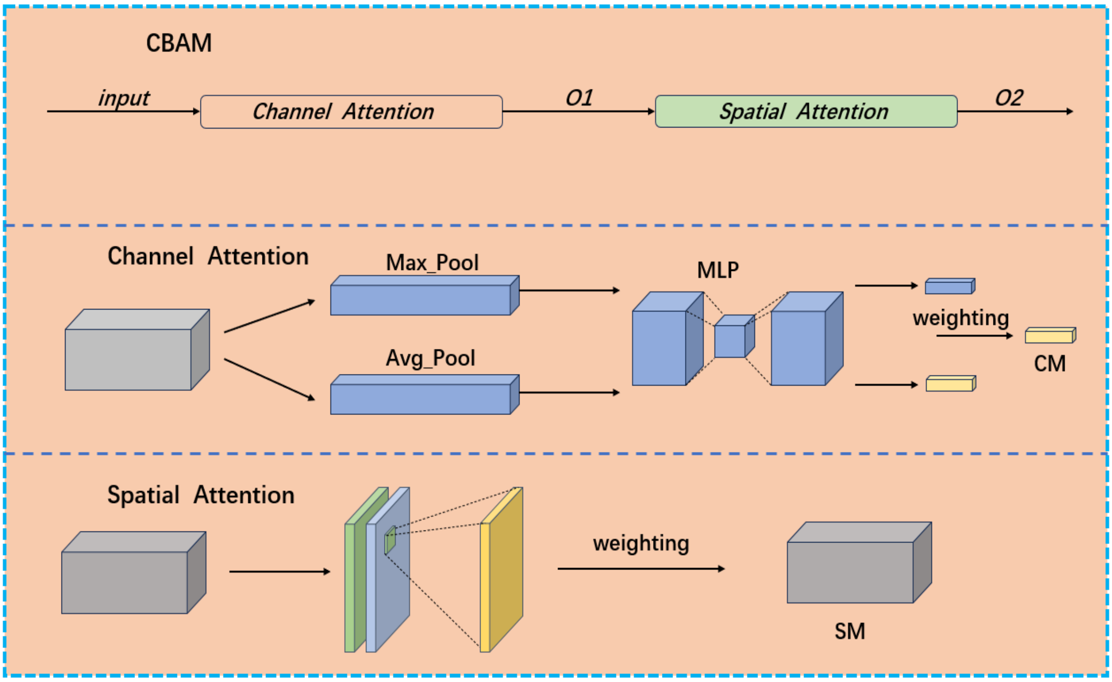

Figure 2: The structure of Convolutional Block Attention Module (CBAM)

CBAM (Convolutional Block Attention Module) is a sophisticated and efficient attention mechanism[14] that enhances the model's ability to recognize and utilize key image features by combining channel attention and spatial attention mechanisms. Its main structural components are shown in Figure 2. The input feature map is subjected to global average pooling and global maximum pooling to obtain one-dimensional feature vectors, respectively; Two feature vectors pass through an MLP with weight sharing, and then the weights are added together. Finally, the sigmoid activation function is recorded to

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obtain the channel attention mechanism. The detailed calculation formula is as follows:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (1)$$

The CBAM structure consists of two independent modules used sequentially[15]: one is the channel attention module, and the other is the spatial attention module. These two modules respectively process the channel and spatial information of the feature map to enhance the expressive power of the features. The core task of the channel attention module is to identify which channels (i.e., which feature types) in the feature map make a significant contribution to the final task and give these channels greater emphasis. The spatial attention module focuses on discovering which regions (i.e., which spatial positions) in the feature map contain more important information, and enables these regions to receive more attention during processing. Through the successive operation of these two modules, CBAM is able to extract and optimize the expression accuracy of features, thereby enhancing the performance of the model in prediction tasks.

2.3 The overview of Defeat-YOLO

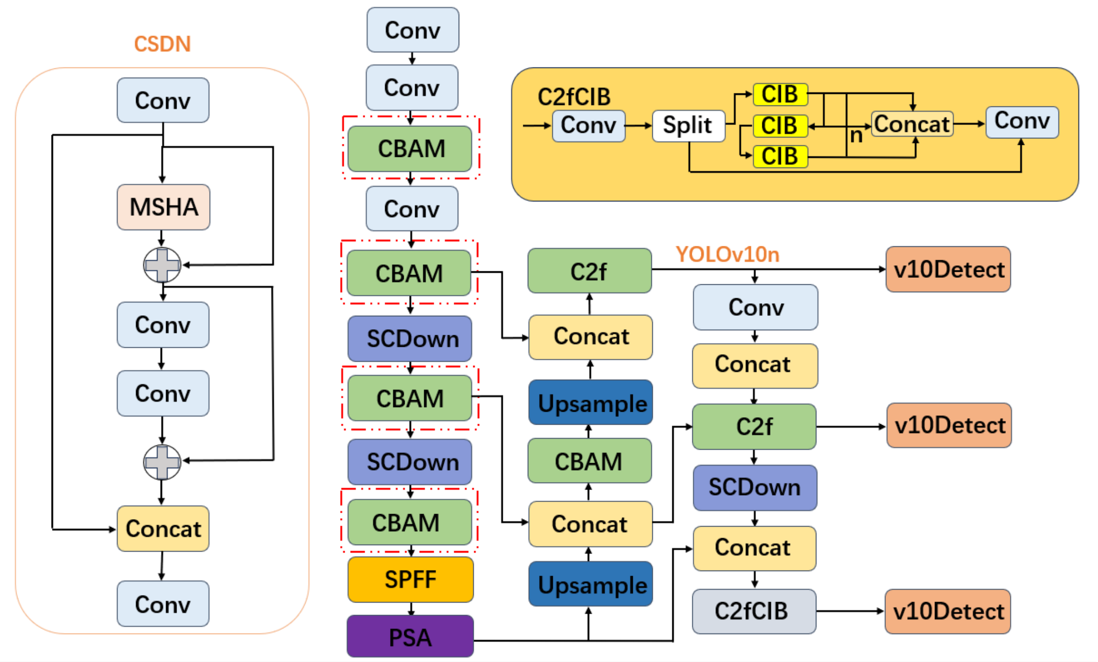

Figure 3: The structure of Defeat-YOLO

CBAM (Convolutional Block Attention Module) is an effective attention mechanism that, when combined with object detection models such as YOLOv10, can improve its performance[16], especially in defect detection tasks. CBAM can adaptively focus on more important features in an image by weighting the attention mechanisms of channels and spaces. This means that in defect detection, the model can better identify and distinguish defect areas, thereby improving the accuracy of detection. In defect detection, background noise and lighting changes may affect the detection performance. CBAM can help the model filter out unimportant features and focus on more discriminative features, thereby improving the robustness of the model in various environments. Seat belt defects are usually small and subtle features, and CBAM can help YOLOv10 better detect these small targets and reduce missed detection rates by weighting the more important parts in the feature map. By capturing spatial attention, contextual relationships can be better understood, which is particularly important in defect detection because defects often require judgment based on the surrounding environment. The addition of CBAM can effectively enhance the ability to understand contextual information. By selectively focusing on important features, CBAM can reduce unnecessary information interference, thereby lowering false detection rates and ensuring high reliability of detection results. As shown in Figure 3, Defeat YOLO achieved more accurate industrial defect detection by fine-tuning the structure of YOLOv 10.

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3. Experimental results

3.1 Experimental Deployment Details

In this study, we used NVIDIA GeForce RTX 2080 SUPER GPU to implement the model. The network parameters of the model are initialized based on a normal distribution. The stochastic gradient descent (SGD) algorithm was selected as the optimizer for the model, with a momentum of 0.9 and a weight decay of 0.0001. During the training process, we used a batch size of 4 and set the initial learning rate to 0.01. The entire training process consists of 100 cycles, and at the 24th and 30th cycles, the learning rate was reduced by 0.1 times respectively.

During the training and testing phases of the model, all input images were resized to a size of 640x640 pixels. In addition, image enhancement techniques were applied, including horizontal and vertical flipping with a probability of 0.5, to enhance the model's generalization ability. In short, we optimize our deep learning model by using refined parameter initialization and adjustment strategies on high-performance GPUs, as well as employing effective image enhancement techniques.

3.2 Datasets and Evaluation Metrics

The dataset used in this study consists of seat belt defect samples collected in real industrial production environments. In order to improve the diversity of data, we performed scene transformations and lighting condition adjustments on the images, ultimately generating 1200 images. Figure 4 shows the samples of these images. We randomly selected 30% of the data as the test set, and the remaining images were used for model training.

Figure 4:Image of seatbelt defect dataset

In order to comprehensively measure the performance of the model, this study mainly used the metric of Mean Precision (mAP), which is calculated based on a confidence threshold of 0.5 to obtain the Average Precision (AP) value. In addition, to evaluate the performance of the model in more detail, we also introduced recall rate, accuracy (precision), and F1 score as supplementary indicators. Through these comprehensive evaluation indicators, we can conduct in-depth analysis of the model's detection capability from multiple perspectives.

3.3 Ablation analysis

Table 1: Ablation analysis

Models	Recall	Precision	mAP
YOLOv10	85.1	86.9	93.3
Defeat-YOLO	91.5(+6.4)	96.3(+9.4)	96.6(+3.3)

The data in Table 1 indicates that compared to the base model YOLOv10, the model integrating CBAM performs better in feature extraction, with a 6.4% increase in recall, a 9.4% increase in accuracy, and a 3.3% increase in average precision (mAP). These results confirm the effectiveness and superiority of Defeat YOLO in seat belt defect detection tasks. By introducing CBAM, the performance of the model

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in identifying and detecting seat belt defects has been significantly enhanced.

3.4 Performance analysis of Defeat-YOLO

In order to further evaluate the performance of Defeat YOLO in object detection, this study compared and analyzed it with several other YOLO series models. The data in Table 2 shows that Defeat YOLO achieved a high score of 96.3% in the key indicator of accuracy, which is the most outstanding performance among all compared YOLO models. When it comes to average accuracy (mAP), Defeat YOLO far outperforms other network models, reaching 96.6%. These comparative results fully demonstrate the significant performance improvement of Defeat YOLO compared to YOLOv6, YOLOv8, and YOLOv5. Through these experimental analyses, we can conclude that Defeat YOLO meets the high-precision requirements for seat belt defect detection. Defeat YOLO has demonstrated superior performance compared to other YOLO models in the identification and detection of seat belt defects.

Table 2: Contrast analysis

Models	Recall	Precision	mAP
YOLOv10	85.1	86.9	93.3
YOLOv8	95.3	95.8	94.9
YOLOv6	91.7	96.2	95.4
YOLOv5	94.0	94.2	94.6
Defeat-YOLO	91.5	**96.3**	**96.6**

4. Conclusion

In order to solve the common problems of missed and false detections in traditional methods for seat belt defect detection, this study introduces deep learning technology for defect detection. In order to further enhance the model's perception ability of semantic features, the CBAM attention mechanism was integrated into the YOLOv10 backbone network, thereby enhancing the model's feature extraction ability and providing spatial semantic weights for 32 times down sampled features. After experimental verification, the enhanced model is called Defeat YOLO and compared with other YOLO algorithms. The results show that Defeat YOLO exhibits superior performance and can fully meet the requirements of seat belt defect detection.

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