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Research on CEL-YOLO Algorithm for Lightweight Detection of Traffic Signs

Fuzhaojin Huang[1,a], Zijian Dong[1,b,*], Lingsheng Liang[1,c] , Xinrui Chen[1,d]

[1]*School of Electronic Engineering, Jiangsu Ocean University, Lianyungang, Jiangsu, 222000, China*
[a]*2023220624@jou.edu.cn,* [b]*1995000021@jou.edu.cn,* [c]*2023220611@jou.edu.cn,*
[d]*2023220620@jou.edu.cn*
**Corresponding author*

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Abstract: Nowadays, in the era of rapid development in the field of intelligent transportation and large information reserves, in order to better adapt to embedded devices and improve the real-time and robustness of intelligent vehicle perception, this paper proposes a traffic sign small target detection algorithm based on YOLOv8 model. First, on the basis of C2f-STAR module, StarNet convolution StarsBlock is added to build C2f-Starsblock, which replaces C2f module in Backbone part of YOLOv8 network to improve the feature representation capability and detection performance of the model. Secondly, based on the BottleNeck of the residual module Faster_Block in FasterNet, the C2f module in YOLOv8 network is replaced, and EMA attention mechanism is added to the C2F-FASTER module to construct the C2f-Faster-EMA module. Improve the ability of C2f module to capture multi-scale feature information; Thirdly, the SPPF module is combined with the large separable Kernel Attention (LSKA) module to construct the SPPF-LSKA module to enhance the feature extraction capability of the model. Finally, a Light Weight Shared Convolutional Detection (LSCD) is added. It can be seen in the CCTSDB2021 traffic sign dataset, finally the improvement of the traffic sign this kind of small target detection accuracy and robustness of the model. To verify the effectiveness of CEL-YOLO, mAP-50 achieves 97.1% in traffic sign detection tasks. When the total number of parameters and calculation amount are reduced by 54.5% and 44.5% respectively, the accuracy remains the same as the original model. The verification results show that compared with the benchmark model, the model is significantly lighter in volume and computation, and is more suitable for small target detection.

1. Introduction

Traffic signs, as an important carrier of road information, bear a vital mission. In the rapid development of artificial intelligence and computer vision today, the text and image information transmitted by these signs can not be underestimated in the field of intelligent driving. Just imagine, behind every sign, there are countless safety hazards and driving guidelines, which are directly related to the safety and efficiency of driving. According to the above problems, this paper designs an efficient and lightweight traffic sign recognition algorithm, which retains the high accuracy of YOLOv8n algorithm, reduces the number of parameters and calculation, reduces the complexity of the algorithm, and improves its real-time performance.

In the study of color detection, HSI color space (hue, saturation and brightness) is an effective detection method. It can identify colors more accurately under different lighting conditions, especially in complex background environments, which provides richer feature information for subsequent deep learning models, and further improves the accuracy of traffic sign detection. Benallal et al. [1] found that the RGB components of traffic signs are significantly different under different illumination at sunrise and sunset. Therefore, the component differences are used to detect traffic signs. Chakraborty et al. [2] first used the YCbCr color space model to eliminate the light sensitivity of segmentation, then counted the color threshold for color segmentation, and then used the boundary distance vector to detect traffic signs. Wang et al. [3] first chose to use HSV spatial color detection, and then used the color information extraction method of adjacent pixels to improve the accuracy of the red bitmap of traffic signs to enhance the detection performance of traffic signs.

With the rapid development of deep learning in the field of computer vision, many excellent object detection algorithms have emerged, which can be divided into two categories: two-stage and single-stage. Compared with the two-stage algorithm, the single-stage object detection algorithm is faster in detection speed, and the network architecture is relatively simple, so it has become a popular research object in various fields. Among them, YOLO algorithm is the most representative single-stage target detection algorithm [4]. By improving the YOLOv8 algorithm, Hong Yan et al. [5] introduced the attention mechanism and modified the detection head to detect foreign bodies in coal mines of different scales. Ye Hanyu et al. [6] introduced lightweight module units and CBAM attention mechanism to improve YOLOv5 algorithm to classify domestic waste. Zheng Wenxuan et al. [7] optimized the YOLOv7 network by introducing MobileNetv3 and NWD small-target detection mechanisms to realize automatic detection of fragrant pear. Wang Hai et al. [8] proposed a CASCAD-RCNN traffic sign detection algorithm that integrated functional pyramid network (an improved version of deep feature information and Gou loss function) in order to enhance the accuracy of small-target traffic sign detection. Wei Tiancheng et al. [9] improved the algorithm based on the faster rcnn network by first using 1x1 convolution to build a multi-channel convolutional network to extract input image features, and then replacing the 5x5 convolution in the faster rcnn with 3x3 convolution to increase the sensitivity of different scales, and integrating deep and shallow features to enhance the algorithm feature extraction. Cheng et al. [10] proposed a faster traffic sign detection algorithm based on local context information (1ocalContext-rcnn), which used the rpn network to extract candidate regions to classify local background information, and set the local background as the extraction candidate region to automatically extract classification information, achieving remarkable results.

Traffic signs are often distinguished by specific shapes and colors so that drivers can quickly understand the relevant information. Earlier studies focused on color, shape, and other characteristic elements. With the continuous development of research, the detection methods of traffic signs have gradually evolved, which are mainly divided into traditional image processing methods, deep learning methods and multi-sensor fusion methods. In terms of precision and lightweight, deep learning methods are superior.

2. The Proposed Method

2.1. CEL-YOLO traffic sign small target detection algorithm

These methods have a good performance in traffic sign detection, but with the development of China's road area, increasing the investment in road signs, there will be a series of problems for the current traffic sign detection network model large volume, many parameters, slow operation and so on. Therefore, this paper proposes the CEL-YOLO algorithm framework based on YOLOv8n, a network architecture with high detection speed and accuracy, as shown in Figure 1. The experimental results of this innovation on multiple data sets fully verify its effectiveness and show excellent performance. While ensuring the accuracy and robustness stability, the parameter number and calculation amount are greatly reduced, and the lightweight of the improved model is achieved. Finally, the validity of the model is verified on multiple data sets. Contributions are as follows:

1) StarNet Convolution StarsBlock is used to build a new C2f-StarsBlock module by combining with C2f in Backbone of the original YOLOv8 model, and this module is integrated into YOLOv8 to improve the feature representation and detection capabilities of the model.

2) EMA [11] (Exponential Moving Average) of attention module was improved on YOLOv8 model, and the exponential moving average of parameters of each Batch was used to update the weight of the model. This allows YOLOv8's attention module to better integrate features of different levels, and reduces excessive updating of parameters. By combining EMA attention mechanism with C2f-Faster module, a new C2f-Faster-EMA module is constructed, and the number of model parameters and calculation amount are greatly reduced.

3) The combination of LSKA [12] attention mechanism and SPPF module helps to better extract feature information from feature maps, so as to enhance the detection performance of the model.

4) The head Detection layer of the network is optimized, and a Lightweight Shared Convolutional Detection (LSCD) architecture is proposed, which not only improves the detection efficiency of the model, but also greatly improves the detection accuracy. By introducing shared convolution and scale layer scaling features, LSCD effectively reduces the number of parameters in the detection head, and enhances the global information fusion ability between feature maps, ensuring high detection accuracy even in complex and changeable weather scenarios.

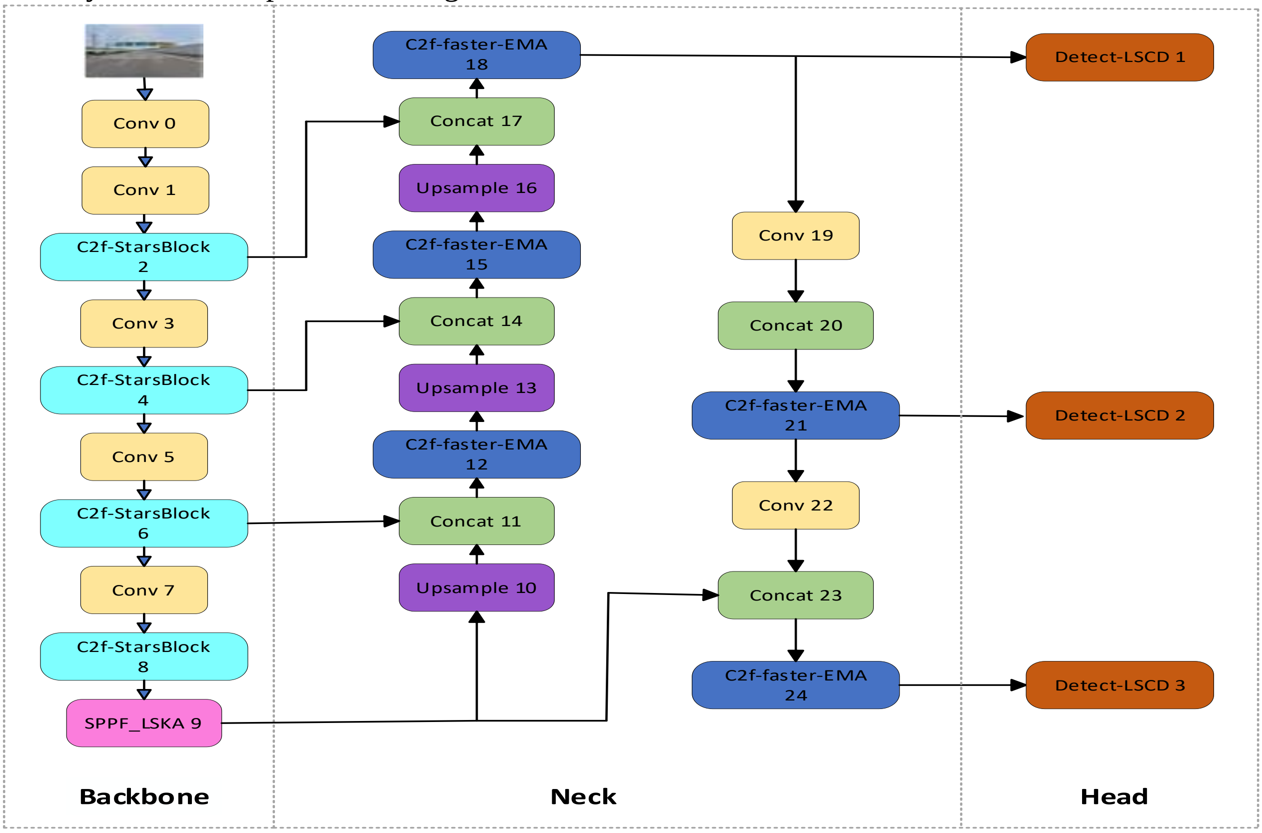

Figure 1: CEL-YOLO detection model framework.

2.2. C2f-StarsBlock module

In 2024, Xu et al. [13] proposed an ability to use Star operation (elite-by-element multiplication) to integrate different subspace features and map inputs to high-dimensional nonlinear feature Spaces without broadening the network. Based on this, StarNet is proposed, demonstrating impressive performance and low latency with a compact network structure and low power consumption. Its schematic diagram is shown in Figure 2.

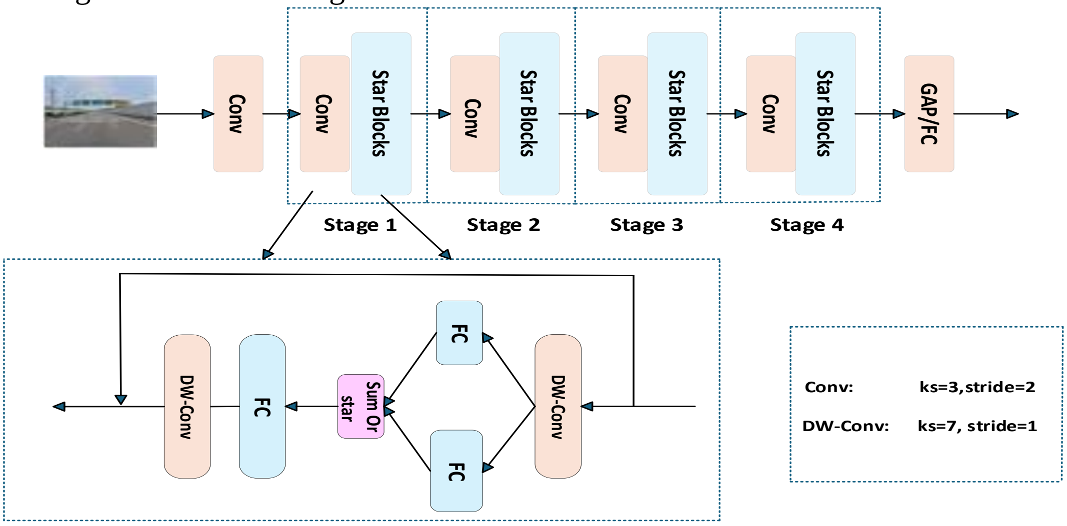

Figure 2: StarNet Framework.

Star operations can map input data to an extremely high-dimensional non-linear feature space. This means that star operations are able to generate rich feature representations, making the model more efficient when dealing with complex data. The star operation differs from the method of increasing the width (or number of channels) of traditional neural networks. It is more like kernel functions (especially polynomial kernel functions), which multiply pairs on different channels, thus achieving nonlinear combinations of features. Star operations are able to work in a compact feature space while benefiting from an implicit high-dimensional feature representation. This is where star operations stand out, providing rich feature representation capabilities without increasing computational costs.

First, an isotropic network named Demo-Net is constructed by stacking multiple DemoBlock behind an interference layer. This includes a layer that reduces the input resolution by a factor of 16 through a depth-separable convolution layer, followed by a series of homogeneous demonstration blocks for feature extraction (see Figure 3), in each of which we apply a star operation or summation operation to fuse features from two different branches.

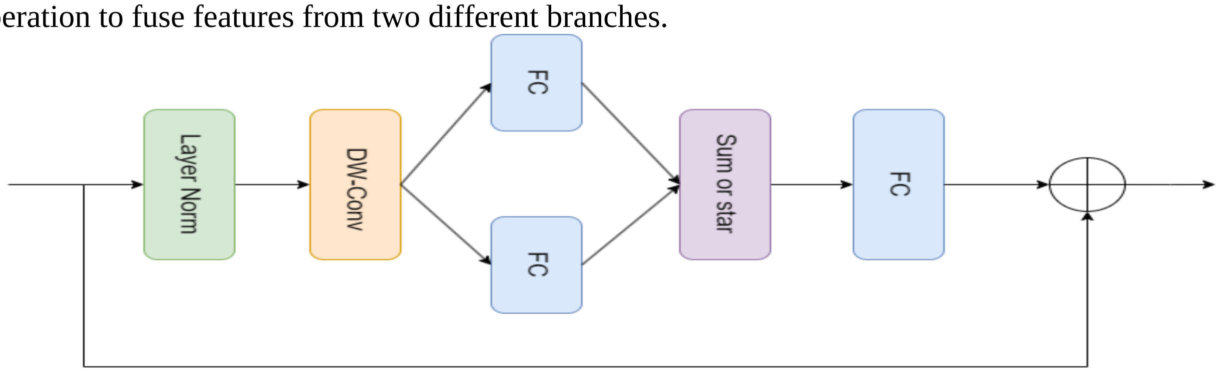

Figure 3: Demo block structure.

StarNet is constructed from a four-level sub-structure, using convolution layer for down sampling and modified demo blocks for feature extraction. To meet efficiency requirements, replace Layer Normalization with Batch Normalization and place it after deep convolution (which can be fused during inference). Inspired by MobileNext [14], deep convolution DW Conv is added at the end of each block. The StarNet framework is shown in Figure 2.

On the basis of C2f-Star module, StarNet Star convolution StarsBlock is referenced to form a high-dimensional nonlinear feature mapping network architecture. The C2f-Starsblock module is constructed and replaced with the C2f module of Backbone in YOLOv8. To improve the feature representation ability and detection performance of the model.

2.3. SPPF-LSKA module

Since the target size of traffic signs is small and the detection environment is complex, the LSKA attention mechanism is introduced into the SPPF module to build the SPPF-LSKA module (see Figure 4). This module can extract information from the feature map more effectively, thus improving the detection performance of the model. LSKA is an improvement on the Attention mechanism of LKSA (Large Separable Kernel Attention) [15]. LSKA module adopts the idea of large convolution kernel decomposition, and standard convolution can be decomposed into three parts: deep convolution, deep extended convolution and point convolution. LSKA splits the convolution of K×K into a deep convolution output of kernel size (2d−1)×(2d−1) to capture local space information. At the same time, the deep convolution compensates the subsequent kernel size to the deep extended convolution, which is used to obtain the global spatial information of the deep convolution output, and finally the output is passed through the 1×1 convolution. The LSKA module uses a large kernel size and focuses more on texture extraction than shape, so it is difficult to distinguish other features in complex textures.

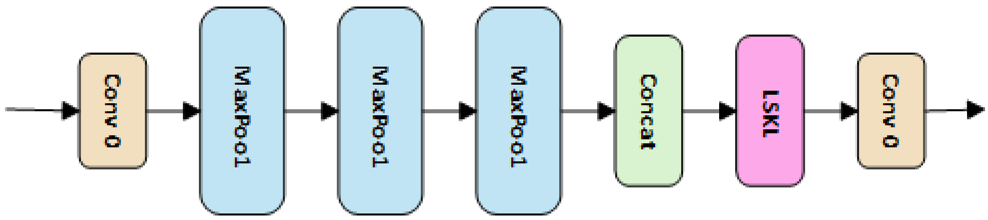

Figure 4: SPPF-LSKA module structure.

2.4. C2f-Faster-EMA Module

In 2023, Chen et al. proposed a new fast neural network (FasterNet), which maintained a high number of floating point operations to a certain extent, and proposed a new Partial Convolution (PConv) [16]. Its schematic diagram is shown in Figure 5. Conventional convolution is used for feature extraction of part of the input channels. In PConv, the calculation is based on the first channel as a reference for the entire feature map, while keeping the number of channels constant. This indicates that the input and output feature maps have the same number of channels. Thus, the floating-point operand (FLOPS) of PConv can be expressed as follows:

$$FLPOPS = h \times w \times k^2 \times c_n^2 \quad (1)$$

Where c_p and c together constitute the separation ratio: $r = \frac{c_p}{c}$ on $r = \frac{1}{4}$, PConv Only Conv $\frac{1}{16}$ FLOPS, PConv also has smaller memory accesses:

$$h \times w \times 3c_n + k^2 \times c_n^2 \approx h \times w \times 2c_n \quad (2)$$

Replace the Bottle Neck module in C2f with the Faster Net Block module to get the C2f-faster module. The Faster Net Block, thanks to PConv convolution, has the advantage of faster speed and fewer parameters with limited loss of accuracy. The BN module in the Faster Net Block is merged with the adjacent Conv module to speed up inference. The Faster Net Block structure is shown in Figure 6.

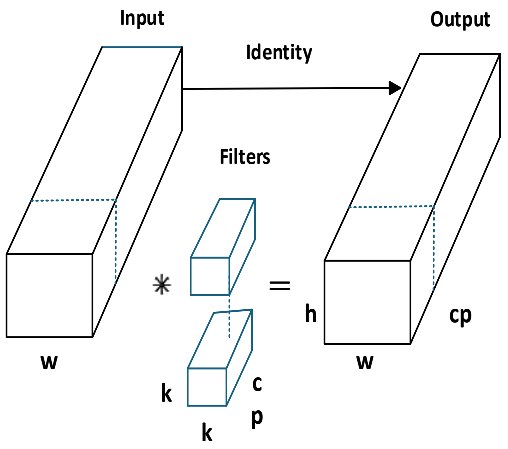

Figure 5: PConv structure.

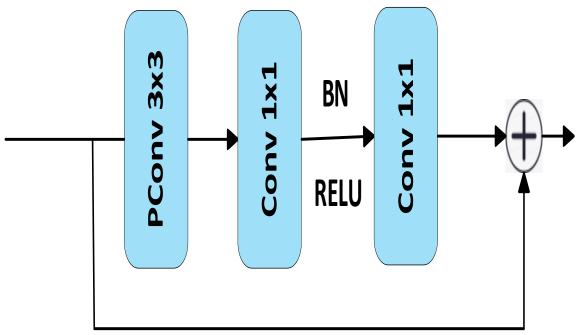

Figure 6: Faster Net Block structure. values.

In this study, EMA attention mechanism is Bottleneck integrated into C2f-Faster to form the C2f-Faster-EMA module, the structure of which is shown in Figure 7. It improves the ability of C2f module to capture multi-scale feature information by optimizing Bottleneck structure.

On the whole, according to previous experience, the C2f-Faster module in neck of YOLOv8 Backbone network was replaced with the C2f-Faster-EMA module. After integrating the EMA attention mechanism, the model can use 1x1 convolution and 3x3 convolution to connect more context information on the intermediate feature map, and further extract and screen the feature information of road signs.

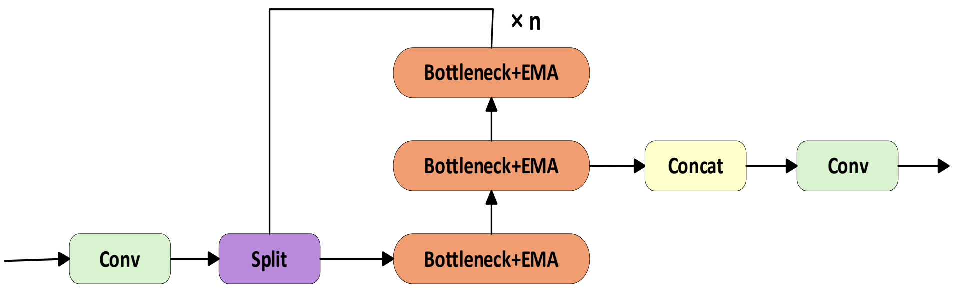

Figure 7: C2f-Faster-EMA structure integrating EMA attention mechanism.

2.5. Detect-LSCD module

YOLOv8 uses the current mainstream decoupling head structure to separate classification and detection heads, but such detection heads have some limitations. First, the number of calculation parameters of detection heads is relatively large, and all three detection heads extract image features through two 3x3 convolution and one 1x1 convolution respectively, resulting in an increase in the number of algorithm parameters. Secondly, the traditional single-scale prediction structure adopted by the original algorithm only predicts from one scale, thus ignoring the contribution of other scale features to the detection. Therefore, we adopted a new LSCD-Head [17] detection head to solve the above problems, and its structure is shown in Figure 8:

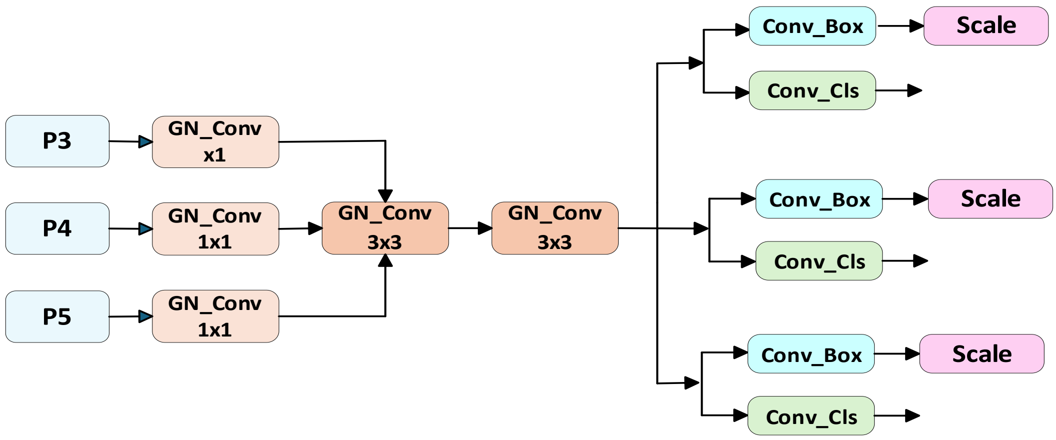

Figure 8: LSCD-Head Indicates the network structure of the detection header.

After the three feature layers output from the neck enter the detection head, each branch first passes through a 1x1 convolution layer to adjust the channel number, and the channel number of the three feature layers is unified into the channel number of the middle layer Chide. In this process, the floating-point arithmetic (FLOPS) of PConv can effectively represent the computational complexity. Next, all feature layers are gathered into a shared convolution module for feature extraction, and the convolution kernel size is set to 3x3. The application of shared convolution significantly reduces the number of parameters and computation, and improves the overall running speed. Finally, a separation is made between the regression branch and the classification branch, in which a 1x1 convolution layer is used to predict the coordinate offset of the bounding box. In order to deal with the challenge of inconsistent target scales detected by different detection heads, the output of the regression branch is also scaled through the Scale layer to accurately locate disease targets of different sizes. At the same time, the classification branch also uses a 1x1 convolution layer to predict the probability of each category, and the convolution layer weights of the two branches are independent so that the model can learn the localization and classification tasks separately [18].

The design of lightweight shared Convolutional detector Head (LSCD) significantly reduces the number of parameters and computational requirements by sharing weighted parameters, thus greatly improving the running speed of the model. In addition, the model can process features of different scales, effectively capture information of different sizes in the image, and enhance the understanding and recognition accuracy of the relationship between objects in the image. Therefore, the application of LSCD to traffic sign image detection is helpful to further improve the inference speed and applicability of the model.

3. Experimental Results and Analysis

3.1. Experimental data set

The experimental data set came from TT100K made by Tsinghua University as the basic data set. The data set contained 221 categories, but due to the needs of the experiment, only 40 categories were obtained at last. The size of the pictures was 1920×1080, with a total of 9126 photos. Among them, there are 7227 training sets and 1899 test sets after pretreatment, which mainly include images of atomization, rainy day, and enhancement data of strong light.

3.2. Experimental configuration

To ensure objectivity, all comparison and validation experiments were performed with the same data set and configuration parameters. In other words, the experimental Settings in Table 1 and Table 2 are kept consistent in order to fairly compare the results under different experimental conditions.

Table 1: Experimental hardware configuration.

Experimental Environment	Configuration
Operating System	Linux
CPU	Intel(R) Xeon(R) Platinum 8255C
GPU	RTX 3080(10GB)
Deep Learning Framework	Pytorch

Table 2: Configuration of training parameters.

Parameter	Configuration
Epoch	300
Batch-Size	16
Initial Learning Rate	0.01
Weight Attenuation	0.005
Optimizer	SGD

3.3. Ablation experiment

In order to verify whether each point of CEL-YOLO network improvement is effective, C2f-Star-EMA module (A), Detect-LSCD module (B), SPPF-LSKA module (C) and C2f-StarsBlock module (D) are added to YOLOv8 network for comparative experiments. The results are shown in Table 3. It can be found from the table that the detection accuracy of CEL-YOLO model is superior to other models except the highest Yolov8n model, and CEL-YOLO model is mostly superior to other models in terms of parameters and computation. Although the CEL-YOLO model may be slightly less accurate than the Yolov8n, the significantly reduced number of parameters and computations more than make up for this slight difference. In fact, the parameters and computational complexity of the model are reduced by 54.5% compared with the original model, and significant lightweight is achieved. This undoubtedly brings many advantages to its practical applications: whether it is deployed on edge devices or in real-time scenarios requiring rapid response, CEL-YOLO can fully leverage its efficient reasoning capabilities to meet demanding performance requirements. Compared with the previous three, the accuracy rate and recall rate of serial number 4 have improved to a certain extent, indicating that the addition of SPPF-LSKA module is effective, which can not only stabilize the accuracy rate and recall rate, but also reduce the number of model parameters and calculation amount to a greater extent.

Table 3: Results of ablation experiment.

Serial number	A	B	C	D	Precision	Recall	mAP	Parameter	GFLOP/s
1	×	×	×	×	95.7	94.1	97.3	3.01	8.1
2	√	×	×	×	93.8	90.5	95.1	2.67	7.4
3	√	√	×	×	94.2	91.3	95.7	2.04	6.3
4	√	√	√	×	94.9	92.7	96.3	2.31	6.5
5	√	√	√	√	95.3	93.8	97.1	1.37	4.5

3.4. Evaluation index

This article uses Precision, Recall, and average, mean precision (mAP@0.5) and mean precision (mAP@0.5:0.95) pairs.The model was evaluated. The accuracy formula is:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

The formula of recall rate is:

$$Recall = \frac{TP}{TP + FP} \tag{4}$$

When calculating mAP@0.5, first set the IoU threshold to 0.5. Then, for each type of sample, its accuracy is calculated. Finally, we average all types of precision to get the value mAP@0.5. In thisarticle, for each IoU threshold, we first calculate the accuracy and recall curves for each category.Next, we calculate the average accuracy under these curves and use these averages as the final result; Then average the average accuracy for all IoU thresholds mAP@0.5, as follows:

$$AP@0.5 = \frac{1}{n}\sum_{i=1}^{n} P_i = \frac{1}{n}P_1 + \frac{1}{n}P_2 + \cdots + \frac{1}{n}P_n \tag{5}$$

3.5. Contrast experiment

In order to verify the superiority of this Model and other current models, accuracy rate, recall rate, average accuracy mean, Parameters and Model size are taken as evaluation indexes. The comparison of YOLOv5s, YOLOv8n, reference [19] under the same environment is shown in Table 2. According to Table 4, the parameters and model size of YOLOv5s are too large to be easily deployed by mobile devices. The CEL model in this paper is slightly lower than the original YOLOv8n, but it has smaller parameters and scale, and other indicators are better than the original YOLOv8n algorithm under the premise of stable accuracy. Compared with recent literatures (such as literature [19]), the algorithm proposed in this paper performs better on most indicators.

Table 4: Comparative experimental results of different models.

Models	Precision	Recall	mAP	Parameter	GFLOP/s
YOLOv5s	94.7	93.5	96.8	3.41	10.3
YOLOv8n	95.7	94.1	97.3	3.01	8.1
Docu[19]method	95.6	94.0	97.0	2.98	7.6
Docu method	96.3	94.9	97.6	2.78	7.3

3.6. Visualization

In this section, in order to demonstrate the detection capability of CEL-YOLO model, different categories of data sets are presented.As shown in Fig. 9, 10 and 11 below, Fig. 9 is the original image, Fig. 10 is the detection result of YOLOv8 model, and Fig. 11 is the detection result of our model.

In summary, the CEL-YOLO model proposed in this paper has good detection performance and is more suitable for small target detection tasks such as traffic sign detection.

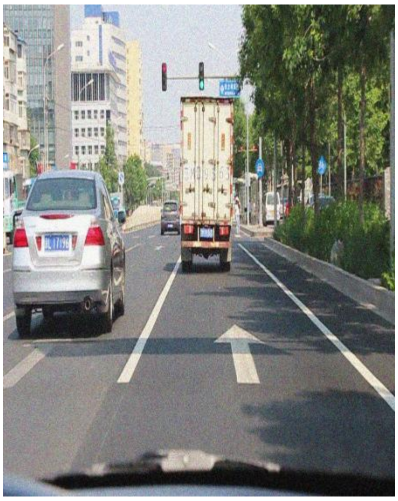

Figure 9: Original image.

Figure 10: YOLOv8 model.

Figure 11: Our model.

4. Conclusion

Through targeted optimization of YOLOv8 algorithm, this paper proposed CEL-YOLO lightweight traffic sign detection algorithm, which effectively solved the problem of balancing real-time and accuracy faced by traditional target detection models in changeable weather scenarios, especially the deployment challenge on resource-limited devices. Firstly, StarNet convolution StarsBlock is added to construct C2f-StarsBlock module to improve the feature representation and detection performance of the model. Secondly, the SPPF and LSKA attention mechanisms were combined to enhance the feature extraction ability of the model, and the C2f-Faster-EMA attention mechanism was introduced to improve the ability of capturing multi-scale feature information. At the same time, the designed LSCD detector head architecture uses the shared convolution mechanism to significantly reduce the detector head parameters and enhance the feature fusion capability, ensuring the high precision detection under complex and changeable weather scenarios. The experimental results show that CEL-YOLO algorithm can achieve significant lightweight of model volume and computation while maintaining or even surpassing the detection accuracy of the original YOLOv8, and provide strong technical support for the intelligent and real-time upgrade of traffic system.

This algorithm has important practical significance for improving the traffic level of urban traffic, road monitoring and other fields. With the continuous iteration and optimization of technology, the future development prospects are broader, CEL-YOLO algorithm is expected to further expand its application scenarios and contribute to the construction of safer and smarter driving.

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