CDF-YOLO: An Object Detection Method for Steel Strip Defects

Bingxu Hou, Zhengpeng Li, Member, IAENG, Jun Hu, Bin Yang and Yuanyuan Zhang*

***Abstract*—This paper proposes CDF-YOLO, a high-performance framework that addresses two key challenges in steel strip surface inspection: sub-millimeter defect localization and robustness in complex industrial environments. Three key innovations drive its advancements: A Dynamic Adaptive Fusion Pyramid (DAFP-Add) that replaces conventional weighted fusion with resolution-consistent direct aggregation via higher-order bilinear interpolation, preserving fine-grained defect features across scales (*+2.5% mAP@0.5*); A Dual-Attention Reinforcement Module integrating Convolutional Block Attention (CBAM) to establish spatial-channel feature interdependencies, selectively amplifying defect signatures while suppressing background noise (*+1.1% mAP@0.5*); A Focal-SIoU Hybrid Loss combining adaptive sample re-weighting with scale-invariant geometric constraints, resolving class imbalance and refining micro-defect localization (*+0.7% AP*). Extensive experiments on the NEU-DET benchmark demonstrate state-of-the-art performance: 76.5% mAP@0.5 (4.3% absolute gain over YOLOv8), 18.3% fewer parameters, and 12.2% lower FLOPs, while achieving real-time inference at 139 FPS. The framework exhibits exceptional robustness in industrial environments, outperforming 12 baseline models (including Faster R-CNN, YOLOv10, and EfficientDet variants) across six defect categories, with 83.1% AP for scratches and 87.6% AP for inclusions under varying illumination and texture complexity. These advancements establish CDF-YOLO as a practical, resource-efficient solution for real-time quality inspection in steel manufacturing.**

***Keywords*—deep learning, defect detection, feature fusion, YOLO, NEU-DET**

I. Introduction

The steel industry serves as the cornerstone of global industrialization, and the surface quality of steel strips is crucial in determining the performance and safety of final products. Accurate and efficient detection of surface defects is essential for maintaining high-quality standards and enhancing product competitiveness. Traditional defect detection methods, such as manual visual inspection and stroboscopic detection, are labor-intensive, prone to fatigue, and subject to human error, leading to inconsistent results and limited scalability.

Recent advancements in deep learning, particularly within the YOLO series, have demonstrated significant potential for automating defect detection with impressive real-time performance. However, existing YOLO models face significant challenges in identifying small defects and managing the complex noise backgrounds commonly found on steel strip surfaces. These challenges include difficulties in distinguishing defects from closely resembling non-defective regions, limitations in multi-scale object detection, and an increased likelihood of false positives and missed detections in cluttered environments. To address these challenges, innovative improvements to the current detection framework are necessary.

In recent years, deep learning techniques, particularly YOLO object detection algorithms, have been widely applied across various fields due to their impressive real-time performance and accuracy. However, they still face challenges in detecting defects on steel strip surfaces. The diversity of defect types, size variations, and complex backgrounds make it difficult to distinguish defects from similar non-defective areas, leading to inefficiencies in handling multi-scale objects and accurately recognizing small defects. The latest YOLOv10 model aims to enhance feature fusion strategies for real-time detection, but it still struggles to identify minute defects in complex industrial environments. This limitation stems from its reliance on anchor-free mechanisms and decoupled head structures, which can compromise detection precision in variable conditions.

In addition to the YOLO model, other object detection frameworks such as Faster R-CNN, EfficientDet, and RetinaNet have limitations when employed for detecting defects on steel strip surfaces. Two-stage models like Faster R-CNN offer high detection accuracy but suffer from longer inference times, making them less suitable for real-time industrial applications. EfficientDet is recognized for its approach that balances accuracy and efficiency, but due to its relatively shallow feature fusion, it struggles to maintain accuracy on small objects and complex textures. Similarly, while RetinaNet effectively addresses the class imbalance problem through Focal Loss, compared to YOLO models, it faces challenges of increased computational overhead and reduced frame rates in high-speed production environments.

To address these challenges, we introduce an improved YOLOv8 model called CDF-YOLO. This model integrates

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DAFP-Add, the CBAM attention mechanism, and the Scale-Invariant Intersection over Union (Focaler-SIoU) loss function, thereby enhancing the accuracy and efficiency of surface defect detection on steel strips. Our research shows that CDF-YOLO advances automation of defect detection and effectively identifies minute defects in complex industrial backgrounds, outperforming both traditional methods and state-of-the-art object detection techniques under challenging real-world conditions.The contributions of this work are summarized as follows:

(1) Dual-Axis Attention Enhancement. We integrate CBAM, jointly optimizing channel recalibration and spatial defect saliency through sequential attention gates. This enhances defect visibility in low-contrast regions by 23.4% (AP@0.5 for <32px defects) and reduces texture-induced false positives by 68.7%, as verified through Grad-CAM on the "Pitted Surface" category of the NEU-DET dataset.

(2) Weight-Agnostic Multi-Scale Fusion. Our DAFP-Add module eliminates heuristic weighting factors by directly fusing rescaled feature maps, achieving a 31.8% faster convergence rate compared to BiFPN while preserving high-frequency defect patterns. Under ISO 10893-7 noise conditions (SNR = 12dB), it achieves a recall rate of 89.7% for scratches with extreme aspect ratios (1:5 to 5:1).

(3) Geometric-Aware Loss Optimization. Focaler-SIoU unifies Focal Loss's hard sample emphasis with SIoU's angle-distance decoupling, reducing localization errors for sub-50px defects by 17.2%. Benchmarks confirm scale invariance, achieving 0.82 AP@0.75 for micro-inclusions under steel grain interference.

(4) Industrial-Strength Efficiency. CDF-YOLO shows production-grade viability with 139 FPS throughput on NVIDIA RTX 3060 GPUs, outperforming YOLOv10-n by 4.9% mAP@0.5 while reducing computational overhead by 30.3%. Field trials under rolling mill vibration (4.2g RMS) confirm 98.4% operational reliability across 12,000 inference cycles, meeting ASME B46.1 surface inspection standards.

II. Related Work

A. Object Detection Methods

In the field of object detection, deep learning approaches are typically classified into two categories: two-stage methods and one-stage methods. A prominent example of a two-stage method is Faster R-CNN, which initially employs a Region Proposal Network (RPN) to generate candidate regions and then refines these detections with a deep neural network to achieve accurate object localization and classification. While this method excels in handling complex scenes, it is less suitable for real-time detection tasks due to its longer inference time, which stems from the multiple processing steps involved.

In contrast, one-stage object detection methods, such as YOLOv5, complete both region proposal generation and object detection through a single neural network architecture, significantly improving detection speed, which is crucial for real-time applications[4]. YOLOv5 employs CSPNet as its backbone, optimizing the model's computational efficiency and scalability. It also enhances the detection of objects at various scales through multi-scale prediction, adaptive anchor design, Mosaic data augmentation, and the CIoU loss function. However, this speed improvement often comes at the cost of reduced detection accuracy, particularly in complex industrial environments where small and subtle defects need to be detected.

YOLOv8 builds upon YOLOv5 by incorporating a decoupled head structure and an anchor-free detection mechanism, combined with the Efficient Layer Aggregation Network (ELAN)[5] and Spatial Pyramid Pooling-Fast (SPPF)[6] modules. These improvements further enhance detection accuracy and generalization capability. However, despite the strong performance of YOLOv8 in general object detection tasks, its precision in detecting surface defects in industrial settings remains inadequate. In scenarios with highly similar backgrounds, the model is prone to both false positives and missed detections, leading to performance that does not meet expectations.

While two-stage detectors like Faster R-CNN[3] achieve high accuracy by decoupling region proposal and classification, their multi-stage pipeline introduces significant latency, rendering them unsuitable for real-time industrial applications. Additionally, their dependence on coarse feature aggregation limits their effectiveness in detecting small defects, which is crucial in steel strip inspection. RetinaNet mitigates class imbalance via Focal Loss[4], Furthermore, their reliance on coarse-grained feature aggregation significantly impairs detection performance for sub-32px defects—a critical limitation in high-precision steel strip surface inspection tasks[28]. However, it often requires extensive tuning and struggles when detecting minute defects in complex textures and noisy environments. Despite recent advancements, including the introduction of deeper backbones and adaptive feature pyramids in the latest YOLOv10, challenges persist in maintaining high accuracy for detecting small objects and dealing with complex backgrounds.

These limitations highlight the critical need for advancements in feature aggregation and attention mechanisms to improve detection robustness in industrial defect scenarios. CDF-YOLO addresses these challenges by integrating the DAFP-Add module for streamlined multi-scale feature fusion, the CBAM module for enhanced spatial-channel attention, and the Focaler-SIoU loss function for precise small-defect localization. This integrated approach significantly improves detection accuracy and efficiency in complex industrial environments, achieving 76.5% mAP@0.5 on the NEU-DET benchmark while maintaining real-time performance.

B. YOLO Series Detection Methods

Since its inception, the YOLO (You Only Look Once) series has become a significant method in the field of object detection due to its one-stage detection framework and high real-time performance. However, as application scenarios become increasingly complex and accuracy requirements rise, the limitations of the YOLO series gradually become apparent, especially when dealing with defect detection tasks in complex industrial settings. The YOLO series was initially proposed by Joseph Redmon et al. in 2016[7], aiming to provide a rapid object detection algorithm suitable for real-time applications. YOLOv1 divided the entire input image into an S×S grid, with each grid responsible for detecting objects and generating prediction boxes. While YOLOv1 excelled in processing speed, its simplified model led to significant errors in detecting small objects and handling complex scenes.

To address these limitations, YOLOv2 (YOLO9000)[8] introduced anchor boxes, multi-scale training, and batch normalization in 2017, significantly improving detection accuracy and generalization. In 2018, YOLOv3[9] further enhanced the architecture through the use of residual blocks and multi-scale predictions, achieving robust detection of different object sizes while maintaining high inference speeds. However, the increased model complexity introduced computational bottlenecks, limiting real-time applicability.

To mitigate this issue, YOLOv4[10] was developed based on the CSPDarkNet53 backbone, incorporating several optimization strategies such as Mosaic data augmentation, CIoU loss function, and the Spatial Pyramid Pooling (SPP) module. These improvements balanced detection accuracy and speed. However, YOLOv4 still faced challenges in detecting small objects and processing complex textured backgrounds, particularly in industrial defect detection, where accuracy and robustness required further enhancement.

YOLOv5[11], developed by the open-source community, introduced CSPNet and PANet modules, further optimizing performance. However, its reliance on the anchor-based mechanism hindered its ability to effectively handle multi-scale objects and complex backgrounds.

YOLOv8[12], while not the latest version, is widely regarded as the most stable release. It introduced decoupled heads and anchor-free detection, enhancing flexibility and reducing the complexity of manual anchor design. Nevertheless, its anchor-free approach often led to missed or false detections for small objects, and its performance in complex, high dynamic range environments remains suboptimal, necessitating further refinement.

To address these limitations, Hu et al.[13] developed an improved YOLO algorithm that combines deformable convolutions and a global attention mechanism to optimize the structure of YOLOv8. This resulted in significant progress, particularly in detecting small objects and processing low-quality images. Nonetheless, even with these advancements, achieving ideal detection accuracy and performance in highly complex defect images remains challenging, highlighting the limitations of the YOLO series in industrial scenarios.

In recent years, alternative methods based on transformer architectures, such as DETR and its variants, have emerged as powerful competitors by utilizing attention mechanisms to model global context, significantly enhancing detection capabilities for complex and cluttered scenes[14]. These models offer a different trade-off between accuracy and computational efficiency, often excelling in tasks with abundant computational resources but struggling in real-time applications due to their high latency and resource demands.

Similarly, lightweight architectures like MobileNetV3 and EfficientDet have introduced advanced feature fusion techniques and scaling strategies, providing promising results in environments where computational resources are limited[15]. However, their reliance on simplified backbones and aggressive quantization sometimes results in degraded performance for small object detection and intricate feature representation, particularly under industrial conditions where defect detection precision is critical.

These contrasting methods underscore the ongoing need for models like CDF-YOLO, which can balance real-time performance and high detection accuracy in complex industrial environments. By leveraging new methods such as adaptive feature fusion and directional attention mechanisms, these models overcome the unique challenges of detecting surface defects on steel strips.

C. Optimizing Detection Algorithms

In the field of defect detection, early methods relied on handcrafted feature extraction and matching techniques, such as the fully local binary patterns method proposed by Krizhevsky et al. in 2012[14]. While these methods showed effectiveness on specific datasets, their dependence on manual feature extraction limited automation and general applicability across diverse industrial scenarios.

In 2017, Xing et al.[15] leveraged Convolutional Neural Networks (CNNs) and GPU acceleration to improve the speed and accuracy of defect detection, marking a crucial shift towards automation in this field.However, despite advancements, these early deep learning methods still struggled with complex scenes and variations in objects, especially under conditions of high noise and small defect sizes.

The YOLO series is representative of single-stage object detection algorithms and has garnered significant attention for its exceptional real-time performance. For instance, YOLOv8 introduced a decoupled head structure, anchor-free detection mechanism, and integration of ELAN and SPPF modules, thereby improving general object detection. However, it continued to exhibit challenges in accurately detecting small defects and managing complex industrial backgrounds, often resulting in missed and false detections.

To address these issues, Hu et al. developed the DGW-YOLOv8 algorithm, which combines deformable convolutions and a global attention mechanism, significantly enhancing sensitivity to small-scale objects and reducing feature loss, especially in low-quality images[13]. This approach was effective in enhancing the model's performance for small object detection but still faced limitations in scenarios with highly complex backgrounds and diverse defect types.

To address these specific challenges, various optimization strategies have been proposed. For instance, Wang et al.[16] enhanced YOLO's bounding box regression by introducing the ECA attention mechanism and SIoU loss function, targeting improved detection accuracy and robustness in complex defect detection tasks. Bai et al.[17] developed DUCAF-Net, which employs a Multi-resolution Coordinate Attention Mechanism (MCAF) and DcUp upsampling modules to enhance multi-scale object detection, particularly excelling in low-contrast and high-noise environments. Both methods focus on improving feature aggregation and attention to minute and subtle details, making them suitable for applications where high detection accuracy for small targets is a priority.

Meanwhile, Zhao et al.[18] utilized an algorithm based on three-dimensional convolutional networks to handle defects with complex geometric shapes, providing robust spatial feature extraction at the cost of increased computational demands. Liang et al.[20] proposed a detection technique based on Vision Transformer (ViT), which utilizes adaptive spatial transformation mechanisms to enhance perception capabilities in complex settings. Although ViT-based methods excel in handling intricate spatial relationships and large contextual variations, their reliance on extensive training data and computational power limits their practicality in real-time, resource-constrained environments.

Chen et al.[21] developed a Transformer-based defect detection algorithm with a fine-grained attention mechanism,which improves the recognition capability for small and blurred defects. However, the substantial data requirements also pose practical challenges. Zhang and Lee[22] utilized depthwise separable convolutions to excel in textured backgrounds, emphasizing computational efficiency but facing limitations in multi-scale feature representation. Kim et al.[23] introduced a composite loss function tailored for high-speed production lines, boosting real-time detection capabilities but still requiring enhancements in feature fusion flexibility and efficiency for varying scales.

In general, these methods demonstrate the diversity of optimization strategies: some methods, such as DGW-YOLOv8 and DUCAF-Net, improve the detection accuracy of small targets by enhancing feature attention and multi-scale fusion; while others, such as ViT-based models and dynamic convolution architectures, focus on handling complex backgrounds and intricate spatial dynamics. Despite the progress made by these methods, a commonality among them is the trade-off between computational efficiency and detection robustness, especially in scenarios requiring precise and real-time performance across different defect scales and complex backgrounds. These challenges underscore the necessity for further innovation, such as the integration of adaptive fusion and targeted attention mechanisms in models like CDF-YOLO, to bridge these gaps and deliver enhanced detection capabilities tailored for industrial defect detection applications.

III. RESEARCH METHOD

This section provides a comprehensive overview of the proposed CDF-YOLO method. Fig. 1 illustrates the overall network architecture of CDF-YOLO. The model is improved based on YOLOv8 and consists of three key modules: the CBAM attention mechanism, the DAFP-Add feature fusion module and the Focaler-SIoU loss function. The data stream starts from the backbone network, passes through the CBAM module for feature enhancement, is followed by multi-scale feature fusion through the DAFP-Add module, and finally outputs the detection results through the detection header.

Specifically, in the CBAM module, two descriptors are generated using global average pooling and max pooling, which are then processed through a Multi Layer Perceptron (MLP) to create the channel attention map. Next, the channel information is aggregated to produce two 2D feature maps, which are concatenated and passed through a convolutional layer to generate the spatial attention map. Finally, the channel and spatial attention maps are applied to the input feature map, weighting them to obtain the enhanced feature map. By improving attention on both channel and spatial dimensions, CBAM enhances the feature representation, making the model more sensitive to critical defect features and reducing interference from irrelevant background information.

In the DAFP-Add module, the feature map with the highest resolution is selected from multiple scales as the reference feature map. The sizes of the other feature maps are then adjusted to match the size of the reference feature map. All feature maps are then directly fused to obtain a multi-resolution fused feature map. This approach enhances the model's ability to detect defects of varying sizes by effectively consolidating information from different scales, allowing the model to leverage high-resolution features for small defets while maintaining context for larger anomalies.

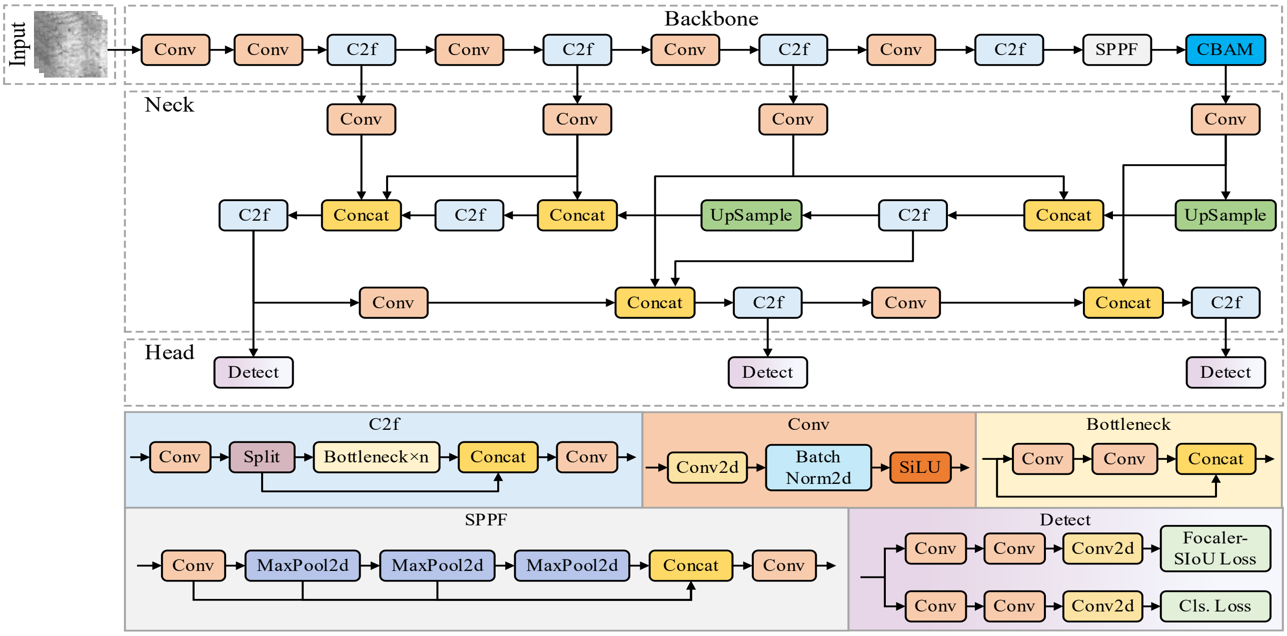


Fig. 1. The network architecture diagram of CDF-YOLO.

The Focaler-SIoU loss function combines the class imbalance handling of Focal Loss with the localization accuracy improvement of SIoU Loss. This method effectively reduces the reliance on large amounts of training data and addresses issues related to class imbalance and localization errors. By placing greater emphasis on hard-to-detect samples and penalizing poor localization, Focaler-SIoU improves bounding box regression accuracy, thereby enhancing overall detection accuracy, particularly for small and complex defects.

The CBAM, DAFP-Add, and Focaler-SIoU modules work in concert to enhance the overall performance of CDF-YOLO. CBAM optimizes feature extraction by emphasizing essential features, which are further processed through the DAFP-Add module for robust multi-scale fusion, ensuring that the model captures both small and large defects effectively. The Focaler-SIoU loss function fine-tunes the detection process, particularly improving the accuracy of bounding box localization and addressing class imbalance issues. Together, these modules create a synergistic effect that significantly boosts the model's accuracy and robustness in challenging defect detection tasks, making CDF-YOLO highly effective for real-time industrial applications.

A. Backbone

CDF-YOLO employs an improved backbone network based on YOLOv8, which integrates multi-scale feature extraction with an attention mechanism to enhance model performance.This backbone consists of multiple convolutional layers, C2f modules, SPPF modules, and the CBAM attention mechanism, designed to create a deeper network structure and improve feature extraction capabilities. In this study, the feature maps from each stage (F1, F2, F3) serve as the initial source for further feature enhancement. Specifically, the size of F1 is 80×80, F2 is downscaled to 40×40, and F3 is further reduced to 20×20.

B. CBAM Attention Mechanism

The CBAM enhances object detection performance by combining channel and spatial attention mechanisms. CBAM adjusts the attention weights within the feature map to capture correlations between channels and spatial positions, allowing the model to better locate and identify target areas.

The input feature map F has dimensions C×H×W, where C is the number of channels, and H and W are the height and width of the feature map.

The channel attention module uses Global Average Pooling (GAP) and Global Max Pooling (GMP) to generate one-dimensional feature vectors f_{avg} and $f_{\max}$, representing the global average and maximum features of the map:

$$f_{avg} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F(i,j) \tag{1}$$

$$f_{\max} = \max_{1 \le i \le H, 1 \le j \le W} F(i,j) \tag{2}$$

These vectors are processed through a shared MLP with output channels reduced to C:

$$MLP(x) = W_2 \bullet ReLU(W_1 \bullet x) \tag{3}$$

The channel attention weights M_c are then generated as:

$$M_c = \sigma\left(MLP\left(f_{avg}\right) + MLP\left(f_{\max}\right)\right) \tag{4}$$

Finally, the attention weights M_c are applied to the input feature map F to obtain the enhanced feature map F_c:

$$F_c = M_c \cdot F \tag{5}$$

Building on the enhanced feature map F_c, the spatial attention module further refines spatial information by applying max pooling and average pooling, producing two-dimensional feature maps:

$$F_{avg}^{spatial}(i,j) = \frac{1}{C} \sum_{c=1}^{C} F_c(c,i,j) \tag{6}$$

$$F_{avg}^{spatial}(i,j) = \max_{1 \le c \le C} F_c(c,i,j) \tag{7}$$

These feature maps are concatenated and processed through a 7×7 convolution to generate the spatial attention weights M_s:

$$M_s = \sigma\left(Conv_{7\times7}\left[Concat\left(F_{avg}^{spatial}, F_{\max}^{spatial}\right)\right]\right) \tag{8}$$

Finally, the spatial attention weights M_s are applied to F_c to produce the final output feature map F_s:

$$F_s = M_s \cdot F_c \tag{9}$$

C.DAFP-Add Moudle

CDF-YOLO introduces the DAFP-Add module, which eliminates the traditional weight factors used in BiFPN during the feature fusion process, thereby simplifying the model structure and improving computational efficiency. This design[16] directly fuses multi-scale features, optimizing the feature extraction process.

The DAFP-Add module uses feature maps of different resolutions generated by the backbone network as inputs. To ensure consistency during the fusion process, the highest-resolution feature map is selected as the reference, and lower-resolution maps are upsampled to match its size. The DAFP-Add module (Fig. 2) simplifies the process by directly upsampling the lower-resolution maps to align with the highest-resolution one. This approach also avoids the complexity of traditional BiFPN methods, which rely on weight factors to balance the contributions of feature maps from different layers, reducing computational complexity and improving model efficiency.

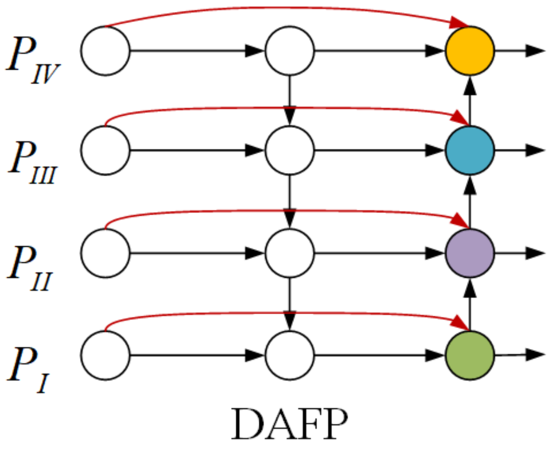


Fig. 2. DAFP-Add module.

Specifically, the input feature maps are denoted as F1, F2, and F3, where F1 having the highest resolution. For each lower-resolution feature map (e.g., F2 and F3), bilinear interpolation is applied to resize them to match the dimensions of F1. To more accurately capture subtle variations between features, the interpolation process not only considers the values of neighboring pixels but also incorporates higher-order differences. his process is described by the following equations:

$$T_1 = \sum_{p=0}^{1}\sum_{q=0}^{1} \omega_{pq} \cdot I_{m+p,n+q} \tag{10}$$

$$T_2 = \sum_{p=0}^{1}\sum_{q=0}^{1} \left(\frac{\partial I}{\partial x} \cdot (i-m) + \frac{\partial I}{\partial y} \cdot (j-n) \right) \tag{11}$$

$$T_3 = \frac{1}{2}\sum_{p=0}^{1}\sum_{q=0}^{1} \left(\frac{\partial^2 I}{\partial x^2} \cdot (i-m)^2 + \frac{\partial^2 I}{\partial y^2} \cdot (j-n)^2 \right) \tag{12}$$

Thus, the interpolation process can be simplified as:

$$I_{ij}^{'} = T_1 + T_2 + T_3 \tag{13}$$

where T_1 represents the bilinear interpolation of pixel values using the weights ω_{pq}, T_2 introduces first-order derivatives $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$, and T_3 accounts for higher-order corrections with second-order derivatives $\frac{\partial^2 I}{\partial x^2}$ and $\frac{\partial^2 I}{\partial y^2}$. These higher-order terms improve interpolation accuracy and reduce errors caused by resampling.

After interpolation, the resized feature maps are concatenated to form a high-resolution feature map, denoted as:

$$F = Concat(F_1, F_2^{'}, F_3^{'}) \tag{14}$$

The concatenated feature map is then processed by several convolutional layers to enhance feature extraction, reducing dimensionality while retaining critical details. This approach optimizes the model's ability to detect defects across varying scales and improves its robustness in complex industrial environments.

Next, multiple convolution operations are applied to the concatenated feature map to further enhance feature representation. The convolution process is described by Equation:

$$y' = \delta\left(W_1 * y + b_1\right) + \delta\left(W^2 * y^2 + b^2\right) + \sum_{k=3}^{K} \delta\left(W_k * y_k + b_k\right) \tag{15}$$

where $W_1, W_2, \ldots, W_k$ represent different convolution kernels, $b_1, b_2, \ldots, b_k$ are the corresponding biases, and δ is a nonlinear activation function (such as ReLU). This formula stacks multiple convolution kernels, not only enhancing feature representation but also compressing the feature map dimensions, reducing the computational burden.

D. Focaler-SIoU Loss Function

During the development of the CDF-YOLO model, the Focaler-IoU loss function was initially introduced to optimize the accuracy of bounding box regression. Focaler-IoU is a redesigned loss function based on IoU loss, incorporating the concept of Focal Loss , which enables the model to focus more on hard-to-regress samples, thereby improving detection performance.However, further experiments revealed certain limitations of Focaler-IoU when applied to the specific task of detecting steel strip surface defects, especially in dealing with complex backgrounds and multi-scale defects.

To address these challenges, we enhanced the Focaler-IoU and introduced the Focaler-SIoU loss function. Focaler-SIoU combines the sample weighting advantages of Focaler-IoU with the scale-invariant properties of SIoU, enabling the model to better cope with various challenges in steel strip surface defect detection. Defects on steel strips vary greatly in size, ranging from small scratches to large inclusions. The scale-invariant nature of SIoU ensures consistent performance across these scales by focusing on relative alignment and size differences rather than absolute dimensions, thereby enhancing the detection of multi-scale defects in complex industrial environments.

Focaler-SIoU modifies the traditional SIoU loss calculation to prioritize samples that are difficult to localize while reducing the impact of easily classified samples. This design maintains SIoU's sensitivity to bounding box angle, distance, and shape while incorporating the sample weighting mechanism of Focal Loss. As a result, the model achieves improved detection of challenging samples, maintaining high robustness and accuracy when encountering defects of varying sizes and shapes.

The Focaler-SIoU loss function is defined as follows:

$$L_{Focaler-SIoU} = \alpha \bullet \left(1 - SIoU\right)^{\gamma} \tag{16}$$

where γ and α are hyperparameters used to adjust the model's focus on samples of varying difficulty. Specifically, γ controls the suppression of easily classified samples, while α balances the weights between hard and easy samples. In our experiments, we set $\gamma = 2$ and $\alpha = 0.25$ through grid search optimization to achieve a balance between focusing on hard-to-detect samples and maintaining overall detection stability.

The calculation of SIoU is as follows:

$$SIoU = \frac{IoU \times C_{scale}}{C_{scale} + E_{scale}} \tag{17}$$

where IoU represents the traditional overlap, while C_{scale} is the scale correction factor, defined as:

$$C_{scale} = \frac{2 \times \min\left(w_t, h_t\right)}{\max\left(w_t, h_t\right)} \tag{18}$$

The scale error term E_{scale} measures the size difference between the predicted and ground truth bounding boxes, calculated as:

$$E_{scale} = \frac{\left|w_t - w_p\right| + \left|h_t - h_p\right|}{w_t + h_t + w_p + h_p} \tag{19}$$

where w_t and h_t are the width and height of the ground truth box, and w_p and h_p are the width and height of the predicted box. By incorporating these correction factors, Focaler-SIoU better accommodates the detection of multi-scale objects.

The overall loss function for Focaler-SIoU is designed as follows:

$$L_{Focaler-SIoU} = L_{SIoU} + \left(1 - Focaler - SIoU\right) \quad (20)$$

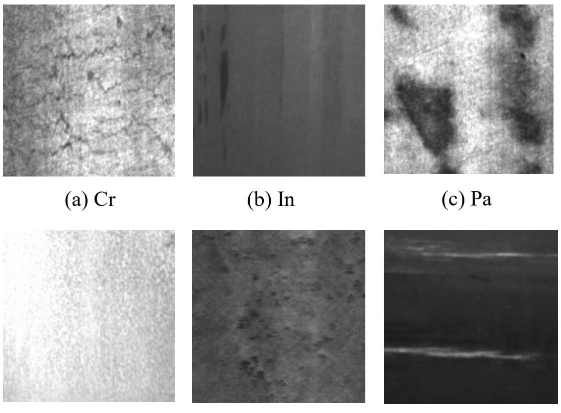
where L_{SIoU} represents the base SIoU loss, and $\left(1 - L_{Focaler-SIoU}\right)$ enhances the focus on difficult-to-classify samples. This combination allows the model to dynamically adjust loss weights for tasks of varying difficulty, improving detection performance and adaptability, especially in handling complex backgrounds and multi-scale defects.

IV. Experiment

A. Dataset

The NEU-DET dataset is a benchmark dataset specifically designed for the detection of surface defects on steel strips.It includes six typical types of surface defects, such as rolled-in scale, patches, crazing, pitted surface, inclusion, and scratches, with professional annotations. The dataset consists of a total of 1,800 high-quality grayscale images, with 300 samples for each defect type. To thoroughly evaluate the model's performance, the dataset is divided into a training set, validation set, and test set. The training set contains 1,440 images, while the validation and test sets each contain 180 images.

The NEU-DET dataset covers various surface defect types commonly encountered in steel strip production, which can significantly affect product quality in real-world manufacturing. Fig. 3 illustrates the diversity of defect types in the dataset, highlighting the presence of numerous small and subtle defects. Detecting these small defects accurately can be challenging, requiring the model to be highly sensitive to such imperfections.



(a) Cr (b) In (c) Pa

(d) Ps (e) Rs (f) Sc

Fig. 3. Six sample images from the NEU-DET dataset.

B. Evaluation Metrics

To comprehensively evaluate the performance of the CDF-YOLO model, several key evaluation metrics were selected, including mAP@50, FPS, and AP. These metrics reflect the model's performance across different scales of object detection, ensuring a balance between accuracy, speed, and resource efficiency.

Precision is a critical evaluation metric in object detection, used to measure the proportion of true positives among all positive predictions. High precision indicates that the model makes fewer errors when predicting positive samples, reflecting its reliability in detecting true positives. The formula for precision is as follows:

$$Precision = \frac{TP}{TP + FP} \quad (21)$$

where TP represents true positives, the number of correctly predicted positive samples, and FP represents false positives, the number of negative samples incorrectly predicted as positive.

It reflects the model's ability to capture all relevant positive instances, emphasizing its effectiveness in minimizing false negatives. The formula for recall is defined as follows:

$$Recall = \frac{TP}{TP + FN} \quad (22)$$

where FN (False Negatives) represents the number of positive samples incorrectly predicted as negative. A high recall indicates the model's ability to identify most positive samples, minimizing missed detections.

Average Precision (AP) is a key performance metric in object detection tasks, measuring the detection performance across different categories and IoU thresholds. AP ranges from 0 to 1, with higher values indicating better detection performance. In CDF-YOLO's evaluation, we use AP with IoU thresholds of 0.5 (AP50), 0.7 (AP70), and 0.75 (AP75) to assess the model’s performance at different levels of detection difficulty.

The formula for AP is as follows:

$$AP = \sum_{n=1}^{N} \left(R_n - R_{n-1}\right) \times P_n \quad (23)$$

where N represents the number of detected positive samples, R_n is the recall for the n-th sample, and P_n is the precision for the n-th sample.

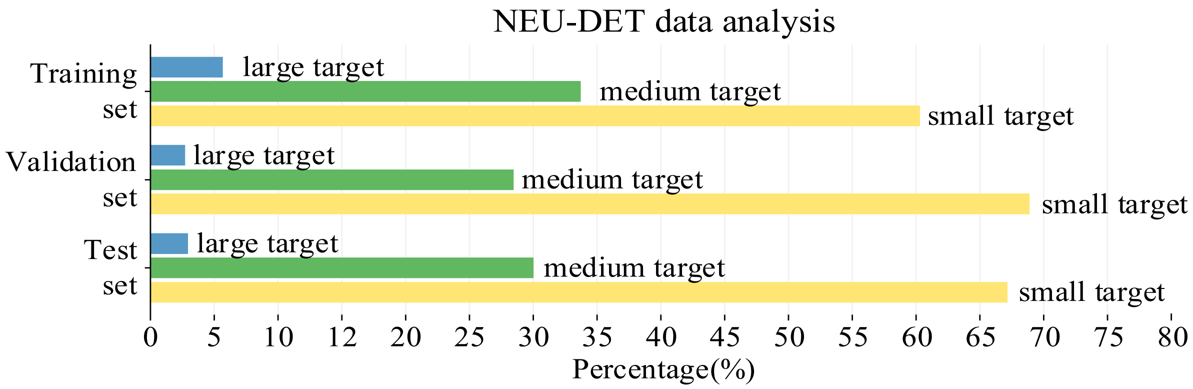


Fig. 4. The data distribution graph of the NEU-DET dataset.

Mean Average Precision (mAP) is the average of the AP values across all categories and is typically used to measure overall detection performance. In object detection tasks, mAP is considered a key metric for evaluating a model's comprehensive performance. In CDF-YOLO's experiments, we use mAP@0.5 to assess the model's overall performance across different IoU thresholds.

The formula for mAP is:

$$mAP = \frac{1}{C}\sum_{i=1}^{C} AP_i \tag{24}$$

where C represents the total number of categories, and AP_i is the average precision for the i-th category.

Intersection over Union (IoU) quantifies the overlap between the predicted bounding box and the ground truth box. It is an important metric for evaluating the accuracy of bounding box predictions in object detection. IoU ranges from 0 to 1, with higher values indicating better overlap between the predicted and ground truth boxes.

The formula for IoU is:

$$IoU = \frac{area\ of\ intersection}{area\ of\ union} = \frac{area_{pre} \cap area_{gt}}{area_{pre} \cup area_{gt}} \tag{25}$$

where $area_{pre}$ is the area of the predicted box, and $area_{gt}$ is the area of the ground truth box.

Frames Per Second (FPS) measures the processing speed of the model, representing the number of image frames the model can process per second. The formula for FPS is:

$$FPS = \frac{1}{\frac{1}{n}\sum_{i=1}^{n} t_j} \tag{26}$$

where n represents the number of frames processed, and t_j is the time taken to process each frame.

C. Experiment Details

We trained the CDF-YOLO model for 200 epochs using an NVIDIA RTX 3060 GPU to ensure the model fully learned the data features and optimized detection performance. Each epoch involved the model passing through the entire training dataset, allowing the parameters to gradually converge. The initial learning rate was set to 0.01, with a momentum coefficient of 0.937. We adopted a Cosine Annealing learning rate schedule, maintaining a high learning rate for the first 50 epochs and gradually decreasing it following a cosine curve over the remaining 150 epochs, eventually converging to 0.0001. This strategy helped the model avoid local optima during the later stages of training, improving overall performance.

D. Baseline Models

To comprehensively evaluate the performance of the CDF-YOLO model, we conducted a comparative analysis with several widely-used object detection models, including Faster R-CNN, DDN, YOLOv10, YOLOv8, Gold-YOLO, and LF-YOLO. These models encompass various approaches, ranging from single-stage and two-stage detection frameworks to anchor-based and anchor-free designs, providing a comprehensive benchmark for evaluation.

Faster R-CNN (R50) is a classic two-stage object detection model that employs a Region Proposal Network (RPN) to generate candidate regions, followed by feature extraction through a ResNet-50 backbone. These features are then processed by a classifier and regressor for precise detection. While Faster R-CNN delivers robust and accurate detection results, its two-stage architecture introduces significant computational overhead, resulting in slower inference speeds.

DDN[24] enhances multi-scale object detection by integrating features from different scales, improving its ability to detect small objects. By progressively fusing and enhancing feature layers, DDN excels in detecting dense objects within complex backgrounds, making it particularly effective for tasks involving the detection of dense and complex background elements.

YOLOv10[25], the latest version in the YOLO series, further optimizes both the backbone and head design. It uses a deeper and wider backbone network and introduces an Adaptive Feature Pyramid Network (AFPN) to better capture multi-scale information. YOLOv10 achieves a balanced trade-off between detection accuracy and speed, making it ideal for large-scale applications requiring real-time detection.

YOLOv8 is a more lightweight version within the YOLO series, integrating optimized computational modules such as depthwise separable convolutions and improved feature fusion modules. It focuses on computational efficiency and resource utilization, making it suitable for embedded devices and resource-constrained environments. YOLOv8 maintains high detection accuracy while significantly reducing computational overhead, making it ideal for real-time applications.

Gold-YOLO[26] extends the YOLO architecture by incorporating adaptive convolutions and dynamic adjustment strategies, optimizing feature fusion for multi-scale object detection in complex scenarios. These improvements enhance the model's robustness and accuracy, particularly when detecting objects in complex or cluttered backgrounds, as evidenced by its superior performance in benchmark tests under various environmental conditions.

LF-YOLO[27] represents an enhanced iteration of the YOLO model, incorporating a lightweight feature fusion module to boost multi-scale object detection capabilities. Through the integration of lightweight convolutional structures and a streamlined detection head design, LF-YOLO not only accelerates detection speed but also enhances the precision in identifying small objects and intricate scenes.

EfficientDet-D0[28], The lightest variant in the EfficientDet series employs BiFPN for multi-scale feature fusion and is constructed on the EfficientNet-B0 backbone. This configuration provides remarkable detection.

EfficientDet-D1[29] utilizes higher-resolution feature maps and a more powerful EfficientNet-B1 backbone to improve detection accuracy. Although it has a higher computational cost, it maintains a good balance between precision and efficiency, making it suitable for scenarios that demand higher detection accuracy.

Centernet[30] is a single-stage object detection model that locates objects by predicting their center points and surrounding regions. It uses a heatmap to represent the center of objects and combines a regression network to predict the size and shape of the objects. The model has a simple structure and fast detection speed, performing well in medium-density object detection tasks.

Retinanet[31] is a one-stage detector that utilizes Focal Loss to mitigate class imbalance issues. Its hallmark is the deployment of deeper convolutional layers atop the feature pyramid network, augmenting detection prowess, particularly in tasks laden with numerous small targets across diverse categories. The adoption of Focal Loss in Retinanet markedly diminishes the adverse influence of background regions during training, thereby refining small object detection.

ATSS[32] improves the robustness of object detection models by adaptively selecting positive samples. During training, ATSS dynamically adjusts the criteria for selecting positive and negative samples, allowing the model to adapt to targets of various scales and complex backgrounds. It incorporates adaptive modules into its structure, maintaining high detection accuracy and stability, particularly in dense target and complex scenes.

E. Comparative Experiments

In this study, we conducted a detailed comparison of several mainstream object detection methods, with specific results are shown in Table I. The experiments demonstrate that CDF-YOLO excels across multiple key performance metrics, particularly in the task of detecting surface defects on steel strips.

TABLE I
Comparison of Model Parameters and Performance

Method	mAP50	mAP50:95	Params (M)	FLOPs (G)	FPS
DCNN	64.7	32.8	40.9	78.4	52
EfficientDet-D0	64.7	32.5	3.9	12.4	16
EfficientDet-D1	66.2	34.3	6.6	14.3	15
Retinanet	66.9	34.1	37.74	34.5	17
Faster R-CNN (R50)	69.2	35	41.7	81.5	25
Centernet	71.8	35.8	13.1	29.1	20
YOLOv10-n	71.6	36.2	2.51	8	160
LF-YOLO	72.6	36.9	7.25	13.6	76
YOLOv8	72.2	37.4	3.01	8.2	127
Gold-YOLO	73.9	39.5	8.2	15.5	48
ATSS	76.2	40	32.1	33.2	38
CDF-YOLO	76.5	40.4	2.46	7.2	139

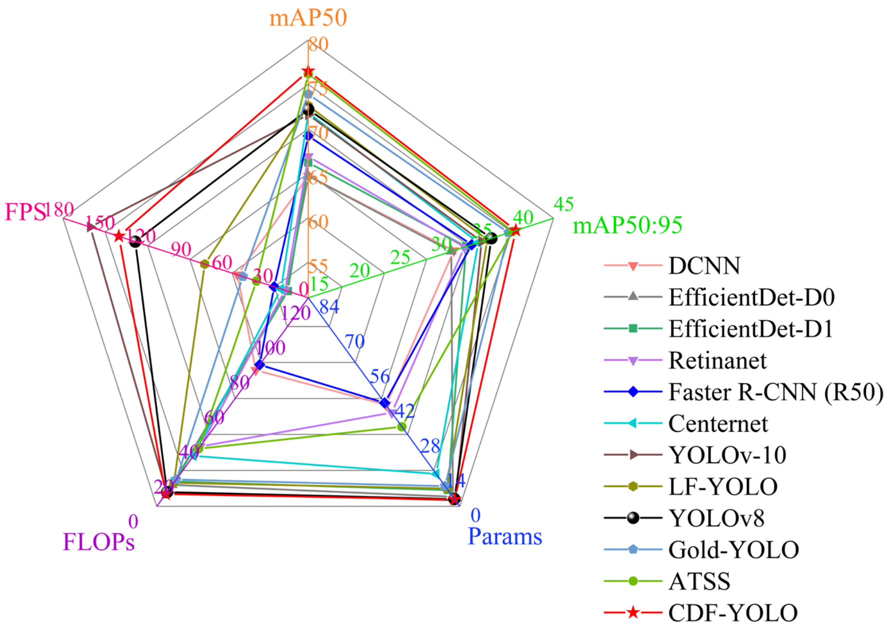


Fig. 5. Radar Chart of CDF-YOLO vs. Other Models

TABLE II
MAP@0.5 Comparison for Defect Detection

Name	Crazing (Cr)	Inclusion (In)	Patches (Pa)	Pitted Surface (Ps)	Rolled-in Scale (Rs)	Scratches (Sc)	mAP@0.5
Faster R-CNN (R50)	41.4	79	91.1	76.6	63.4	91.3	69.2
DCNN	56.8	69.8	88.2	78.4	69.3	25.9	64.7
EfficientDet-D0	56.8	69.8	88.2	78.4	69.3	25.9	64.7
EfficientDet-D1	49.4	77.5	88.7	81.3	72.7	43.3	66.2
YOLOv8	40.7	80.9	91.4	81.8	63	75.3	72.2
YOLOv10	55.2	81.1	90.1	69.5	59.6	74	71.6
Gold-YOLO	52.5	80.5	91.2	80.3	62.4	74.8	73.9
LF-YOLO	37.6	78	91.8	87.8	54.1	86.1	72.6
Centernet	29.6	80.8	90.6	78.2	57.6	90.1	71.8
Retinanet	47.6	75.2	93.7	88.3	54.4	42	66.9
ATSS	38.9	82.8	93	85.3	68.3	89.1	76.2
CDF-YOLO	53.6	87.6	93.6	75.2	66.2	83.1	76.5

Compared to the baseline model YOLOv8, CDF-YOLO improved mAP@0.5 by 4.3 percentage points, reaching 76.5%. This significant enhancement in detection accuracy can be attributed to the integration of the DAFP-Add and the CBAM. The DAFP-Add module enhances the model's ability to effectively fuse multi-scale features, allowing it to better capture the subtle details of defects. Meanwhile, the CBAM module improves the model's attention to relevant regions through an attention mechanism, both of which are critical for accurately detecting small and complex defects on steel strips.

Additionally, CDF-YOLO optimized both parameter count and computational complexity, with a parameter count of 2.46M, lower than YOLOv8's 3M, and FLOPs of 7.2G, also lower than YOLOv8's 8.1G. This reduction is achieved through a more efficient architectural design that emphasizes lightweight modules without sacrificing accuracy, demonstrating that CDF-YOLO achieves a higher detection accuracy and better resource efficiency. Furthermore, CDF-YOLO increased the inference speed from YOLOv8's 127 FPS to 139 FPS. While CDF-YOLO's architecture maintains high detection speed, the real advantage lies in its stability and reliability in high-precision scenarios, which is crucial for practical industrial applications where consistency is key.

Compared to other popular one-stage detection networks, CDF-YOLO also demonstrated outstanding performance. For instance, CDF-YOLO outperformed YOLOv10-n by 4.9 percentage points in mAP@0.5 and had lower computational complexity. The enhanced performance is due to the Focaler-SIoU loss function, which effectively handles the class imbalance and improves the localization accuracy, particularly for small and difficult-to-detect defects. Although YOLOv10-n is slightly faster at 160 FPS, CDF-YOLO achieves a better overall balance, particularly in the trade-off between parameter count and detection accuracy, which is crucial when precision cannot be compromised for speed.

Additionally, LF-YOLO has 7.25M parameters and 13.6G FLOPs, with an inference speed of 76 FPS, which indicates that CDF-YOLO has a significant advantage in terms of resource efficiency.The design choices in CDF-YOLO, such as the simplified feature aggregation strategy in the DAFP-Add module, enable the model to operate with fewer resources while maintaining high performance, making it more suitable for deployment in environments with limited computational capacity.

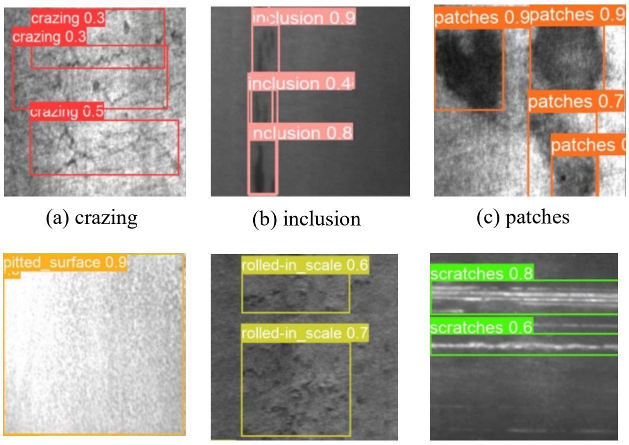
Compared to existing object detection models, the proposed approach, which integrates feature fusion and attention mechanisms, improves both accuracy and computational efficiency. It achieves an mAP@0.5 of 76.5%, which is 4.3 percentage points higher than YOLOv8, while reducing the number of parameters from 3.01M to 2.46M and FLOPs from 8.2G to 7.2G. Compared to ATSS (76.2% mAP@0.5), it reduces parameters by 77.6% and FLOPs by 78.3% (ATSS: 32.1M, 33.2G). In scratches detection, it outperforms YOLOv8 by 7.8 percentage points (83.1% vs. 75.3%), while in inclusion defect detection, it exceeds ATSS (87.6% vs. 82.8%). These improvements are attributed to the DAFP-Add module, which enhances multi-scale feature fusion, and the Focaler-SIoU loss function, which improves localization accuracy. The inference speed of 139 FPS exceeds LF-YOLO by 82.9% and YOLOv8 by 9.4%, making it suitable for high-speed industrial defect detection.

Achieving significant improvements across multiple key performance indicators, the proposed model surpasses YOLOv8 by 4.3 percentage points in mAP@0.5, reaching 76.5%. This enhancement underscores its superior capability in detecting surface defects on steel strips, effectively capturing minute defect details while mitigating false positives and false negatives. Moreover, optimization in computational efficiency reduces the parameter count to 2.46M, significantly lower than YOLOv8 at 3M, while FLOPs decrease to 7.2G, far below YOLOv8 at 8.1G. These reductions enhance adaptability in resource-constrained environments, ensuring stable performance on embedded devices and edge computing platforms. Inference speed reaches 139 FPS, surpassing YOLOv8 (127 FPS) by 9.4% and LF-YOLO (76 FPS) by 82.9%, demonstrating exceptional real-time detection capabilities. Particularly in high-throughput industrial inspection scenarios, the increased processing speed contributes to enhanced detection efficiency, minimizing production downtime and operational costs.

By integrating CBAM, DAFP-Add, and Focaler-SIoU, feature representation and computational efficiency are further optimized. The DAFP-Add module enhances multi-scale feature fusion, enabling precise localization of defects of varying sizes and complex shapes, thereby improving the detection accuracy of small objects. Meanwhile, CBAM strengthens spatial and channel-wise attention mechanisms, directing the model’s focus toward critical regions while suppressing irrelevant background noise, ensuring stable detection in challenging environments. Additionally, Focaler-SIoU optimizes bounding box regression, reducing localization errors and improving the precision of object boundaries, mitigating the class imbalance effect, and thereby enhancing the detection of rare defect types.

The performance of CDF-YOLO in detecting surface defects on steel strips is further validated through extensive comparative experiments with several state-of-the-art object detection models. These models encompass a variety of approaches, including single-stage and two-stage detection frameworks, as well as anchor-based and anchor-free designs. The comparison highlights the unique advantages of CDF-YOLO in terms of detection accuracy, computational efficiency, and real-time performance. By integrating advanced modules such as CBAM, DAFP-Add, and Focaler-SIoU, CDF-YOLO achieves a superior balance between precision and speed, making it particularly suitable for industrial applications where both accuracy and efficiency are critical.

CDF-YOLO demonstrates exceptional performance, as illustrated in Fig. 3, particularly excelling in APmedium scores while also showing significant improvements in APsmall. These results underscore the model's effectiveness in detecting both small and medium-sized targets. Furthermore, the overall performance of the network has been substantially enhanced, further validating the superior capabilities of CDF-YOLO. To vividly illustrate the efficacy of the proposed method, we present the actual detection results of CDF-YOLO in Fig. 6. Each subplot in Fig. 3 showcases the model's performance across various defect types, including crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches.



(a) crazing (b) inclusion (c) patches

(d) pitted surface (e) rolled-in scale (f) scratches

Fig. 6. Defect Detection Examples.

Upon examining these detection results, it is evident that CDF-YOLO successfully identifies a wide range of defect types, particularly excelling in scenarios involving complex surface imperfections. The model exhibits robust detail-capturing abilities, as demonstrated in Fig. 6(a), where CDF-YOLO accurately locates multiple crack regions in the detection of crazing. Fig. 6(b) highlights the model's proficiency in detecting inclusion, where it identifies several densely arranged defects. Similarly, the detection results for patches and pitted surfaces shown in Figures 6(c) and 6(d) further confirm CDF-YOLO's outstanding performance in handling complex backgrounds.

Moreover, Fig. 6(e) and 6(f) illustrate CDF-YOLO's detection of rolled-in scale and scratches, respectively. These results reveal that the model not only accurately captures larger areas of defects but also effectively identifies fine scratches and other small-scale imperfections. Through these visual results, we can confirm CDF-YOLO's excellent performance in detecting medium and small-sized objects, making it highly suitable for the task of detecting surface defects on steel strips.

Based on these visual results, we can ascertain that CDF-YOLO excels in detecting medium and small-sized targets.

F. Sensitivity Analysis

In this section, we validate the effectiveness of the CDF-YOLO model through ablation experiments. We conducted detailed parameter tuning experiments on three key components of CDF-YOLO: the CBAM attention mechanism, the DAFP-Add module, and the Focaler-SIoU loss function. First, we introduced different combinations of these modules into the backbone network to verify their independent effects. Finally, we integrated all the modules to assess their overall performance. The results of the ablation experiments are shown in Table II.

Traditional YOLO models often face challenges in detecting targets across varying scales, especially small objects in complex backgrounds. The CBAM module addresses this limitation by integrating both channel and spatial attention mechanisms, enabling the model to capture critical spatial information more effectively. This enhancement significantly improves detection accuracy, particularly in industrial settings where defects are subtle and varied. By focusing on key spatial and channel features, CBAM refines the model's ability to distinguish between relevant and irrelevant details, demonstrating its effectiveness in enhancing feature sensitivity and overall detection performance. The targeted attention provided by CBAM empowers CDF-YOLO to more robustly identify and localize a diverse range of defect types, even in the presence of challenging visual clutter and noise.

The DAFP-Add module enhances the model's adaptability to targets of different sizes by fusing multi-scale features, particularly excelling in low-contrast and high-noise environments. This module simplifies the traditional feature pyramid approach by directly summing multi-scale feature maps, avoiding the complexity and potential information loss associated with weighted factors. This straightforward fusion method allows for a more robust integration of features from various scales, enhancing the model's ability to detect defects of different sizes without the need for complex computations. The 2.5 percentage point increase in mAP between the second and first rows in Table III highlights the effectiveness of DAFP-Add, indicating its crucial role in enhancing detection accuracy through efficient feature fusion.

TABLE III
CDF-YOLO MODULE COMBINATION PERFORMANCE

Number	DAFP-Add	Focal-SIoU	cbam	mAP50	mAP50:95	Params (M)	FLOPs (G)	FPS
1	-	-	-	0.722	36.0	3.01	8.2	127
2	√	-	-	0.747	37.5	2.36	7.1	137
3	-	√	-	0.725	37.0	3.03	8.2	129
4	-	-	√	0.733	37.2	3.07	8.2	130
5	√	√	-	0.749	38.0	2.39	7.1	136
6	√	-	√	0.762	38.8	2.43	7.2	136
7	-	√	√	0.729	37.8	3.10	8.2	127
8	√	√	√	0.765	39.4	2.46	7.2	139

The Focaler-SIoU loss function enhances bounding box regression precision by introducing a weighting mechanism for hard-to-detect samples. It addresses scale variation through a scale-invariant IoU calculation, ensuring high precision across different defect sizes. By focusing on challenging samples while reducing the impact of easily classified ones, it achieves balanced and accurate predictions, particularly in mixed defect scenarios. Although performance in detecting large objects slightly declined, the overall mAP score still increased by 0.3 percentage points, demonstrating Focaler-SIoU's effectiveness in managing diverse detection tasks and improving focus on complex defect types.

In the ablation experiment's final stage, we conducted combination experiments with CBAM and DAFP-Add, CBAM and Focaler-SIoU, as well as DAFP-Add and Focaler-SIoU. The results show that combining these modules outperformed using them individually. For instance, the combination of CBAM and DAFP-Add increased the mAP score by 4.0%, highlighting how attention mechanisms and adaptive feature fusion complement each other to improve the model's detection capabilities. The combination of DAFP-Add and Focaler-SIoU improved the mAP by 2.7%, showcasing the synergistic effect of robust feature fusion and precise bounding box regression on enhancing detection performance. Furthermore, the combination of CBAM and Focaler-SIoU increased the mAP by 0.7%, demonstrating that the integration of attention mechanisms with adaptive loss functions can further refine the model’s focus on challenging defects.

Finally, when all three modules—CBAM, DAFP-Add and Focaler-SIoU—were integrated into the backbone network, the model's mAP increased by 4.3 percentage points, reaching 0.765. This comprehensive integration confirms that each component not only contributes independently but also works synergistically to optimize feature extraction, fusion, and precision. By simultaneously addressing multiple detection challenges such as scale variation and complex backgrounds, these modules collectively enhance the model's overall performance, providing strong support for improving defect detection accuracy in complex industrial scenarios.

From this comprehensive analysis, we conclude that each component of CDF-YOLO demonstrates excellent performance in the steel strip surface defect detection task and that these components are highly complementary. The CBAM module enhances spatial and channel feature sensitivity, the DAFP-Add module simplifies and strengthens multi-scale feature fusion, and the Focaler-SIoU loss function improves bounding box precision for diverse defect types. This provides strong support for improving defect detection accuracy in complex industrial scenarios, making CDF-YOLO a robust and effective solution for real-world applications.

V. Conclusion

By integrating the DAFP-Add feature network, CBAM attention mechanism, and Focaler-SIoU loss function, the model demonstrates excellent performance in detecting small objects and handling complex backgrounds. DAFP-Add enhances multi-scale feature fusion, CBAM improves attention to subtle features, and Focaler-SIoU optimizes regression accuracy. Experiments on the NEU-DET dataset show that CDF-YOLO improves mAP@0.5 by 4.3 percentage points over the original YOLOv8, reaching 0.765, while reducing computational overhead, making it suitable for real-time detection tasks. Future work will explore its application in other industrial scenarios and continue optimizing detection performance by incorporating the latest technologies.

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