Fire Detection System Based on YOLOv5 with Attention Mechanism

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Abstract: The increasing frequency of fire incidents in dense urban areas has highlighted the limitations of traditional sensor-based detection systems, such as delayed response and high false alarm rates. To address these challenges, this study proposes an enhanced fire detection algorithm based on You Only Look Once Version 5 (YOLOv5), incorporating a Squeeze-and-Excitation (SE) attention mechanism. The SE module was selected for its effective channel-wise feature recalibration capability and its minimal computational overhead, making it ideal for deployment on edge devices in real-time scenarios. Experimental results demonstrate that the proposed method achieves a precision of 0.87, recall of 0.86, and mAP@0.5 of 0.91, with a mAP@0.5:0.95 of 0.42, indicating robust performance under stricter evaluation criteria. The model maintains high computational efficiency, exhibiting strong potential for practical, real-time fire detection applications.

Keywords: YOLOv5, fire detection, Squeeze-and-Excitation (SE) attention mechanism, target detection

1. Foreword

Fire is a sudden and destructive disaster that frequently occurs in urban development, industrial manufacturing, forest conservation, and other sectors. According to the 2024 China Fire Statistics Yearbook [1], over 200,000 fire incidents occur annually nationwide, causing staggering casualties and property losses. Therefore, developing efficient, accurate, and real-time automatic fire detection and early warning systems holds significant social importance.

Current mainstream fire early warning systems primarily rely on sensors for localized physical environment monitoring. While this approach offers lower implementation costs, it suffers from limitations such as restricted deployment coverage, slow response times, and poor environmental adaptability. In contrast, image recognition-based fire detection methods enable comprehensive dynamic monitoring through camera footage collection [2]. These systems demonstrate advantages like rapid response and strong adaptability, making them suitable for deployment in urban surveillance systems, forest fire prevention networks, indoor fire suppression systems, and various other scenarios.

The YOLO series has seen rapid advancements in object detection algorithms in recent years. As a mature version within this family, YOLOv5 maintains high detection speed while demonstrating strong performance in small target detection and edge deployment tasks [3–4]. However, due to the highly variable characteristics of fire images—including diverse flame shapes and complex background interference—

YOLOv5 still exhibits limitations in feature extraction capabilities [5]. These shortcomings result in significant detection errors and limited generalization ability.

To address the aforementioned challenges, this paper introduces the Squeeze-and-Excitation (SE) attention mechanism and integrates it into the YOLOv5 network architecture. The SE module enhances the model's ability to represent key regional features by modeling channel feature importance. This study details the structural design of the improved model and demonstrates its effectiveness and superiority in fire detection through a series of experimental validations.

2. Method

2.1. Introduction to YOLOv5 Model

YOLOv5 is an efficient real-time target detection model open-sourced by the Ultralytics team in 2020 [6]. Its core architecture consists of three interdependent modules: Backbone, Neck, and Head. Specifically, the Backbone employs an improved CSPDarknet (Cross Stage Partial Darknet) structure integrated with a Spatial Pyramid Pooling-Fast (SPPF) module [7], endowing the model with robust capability to extract discriminative features (e.g., texture and shape characteristics of fire targets) from input images. Meanwhile, the Neck adopts a Path Aggregation Network (PANet) for bidirectional multi-scale feature fusion, which effectively aggregates shallow detail features and deep semantic features to enhance the model's detection performance on targets of varying sizes (e.g., small smoke plumes and large open flames in urban fire scenarios). Finally, the detection Head is responsible for outputting the final prediction results, including the final classification and positioning results.

YOLOv5 achieves rapid target box matching through the Anchor mechanism and adopts an end-to-end training approach, making it suitable for deployment in various real-time detection systems [8–10]. However, its network architecture has shortcomings in channel information modeling, making it difficult to accurately identify ambiguous and highly variable targets like flames.

2.2. Rationale for Selecting the SE Attention Mechanism

The selection of the SE attention mechanism is primarily driven by the stronger pertinence of channel feature calibration to the recognition of flame and smoke targets, with its mechanism manifested in two specific aspects: first, it strengthens feature channels sensitive to flame/smoke (e.g., channels representing red spectra and brightness information) by enhancing the weights of key channels, thereby highlighting target-related features [11]; second, it weakens redundant channels dominated by background information and noise by suppressing the response of interfering channels, reducing the interference of irrelevant features.

In contrast, the spatial attention mechanism with a fixed region-focused mode has limited adaptability to non-rigid and morphologically variable targets such as flame and smoke—its fixed regional attention logic cannot match the dynamically changing spatial distribution of targets [12], resulting in insufficient robustness of feature extraction.

The experimental results in this paper further verify the effectiveness of this selection: in the target detection task, the model's mAP@0.5 (average accuracy) reaches 0.91, with both Precision and Recall exceeding 0.85. This fully demonstrates that the channel-level feature recalibration capability of the SE module can significantly improve the model's recognition performance for flame and smoke targets.

2.3. The Principle of SE Attention Mechanism

The Squeeze-and-Excitation (SE) module is a channel attention mechanism. The core idea of this mechanism is to assign weights to each channel, so that the model can automatically focus on the channel features more useful for the current task, thus improving the overall recognition performance [13].

The SE module consists of three steps:

Squeeze: It performs global average pooling on the input feature map, compress the two-dimensional feature map of each channel into a value, and obtain the channel description vector;

Excitation: A two-layer fully connected network is used to build nonlinear channel relationship through RELU and Sigmoid functions, and generate the importance weights of each channel;

Scale: The weight is multiplied with the original feature map channel point by point to realize the re-calibration of features.

This module has small parameters and low calculation, which is suitable for embedding into lightweight detection networks such as YOLOv5 without significantly increasing the complexity of the model. The structure of the SE building block is depicted in Fig. 1.

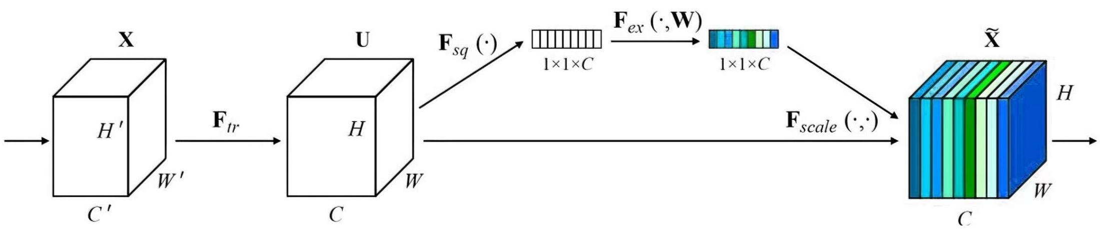

Fig. 1. A Squeeze-and-Excitation block.

2.4. Improved Model Structure

This paper embeds the SE module into the C3 structure unit of the Backbone in YOLOv5 and the Feature Pyramid Network (FPN) feature fusion module in the Neck structure. This approach introduces attention weights in feature maps of different scales, which enhances the model’s perception of high-frequency flame information and suppresses the interference of background information. And Fig. 2 illustrates the process of combing improved YOLOv5 and SE pipeline.

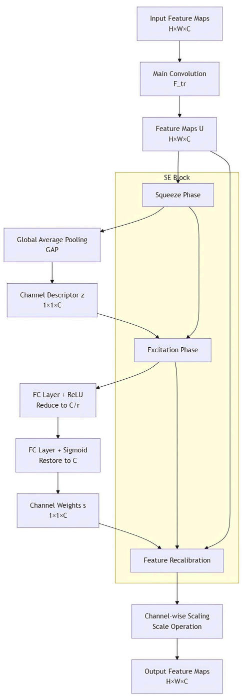

Fig. 2. A flowchart introducing the SE attention mechanism into the YOLO v5.

The improved network retains the structural advantages of YOLOv5, and has a stronger channel selection ability, which can accurately focus on the core area of the flame in fire images and improve detection accuracy.

3. Experiments and Results

3.1. Experimental Setup

Data set: The experimental dataset comprises 8426 manually annotated fire images collected from multiple public repositories and proprietary sources. The dataset includes 5183 flame images and 3243 smoke images, representing various scenarios including indoor fires, outdoor wildfires, and industrial fire incidents—with a typical example of active fire depicted in Fig. 3. The data was randomly split into training (70%, 5898 images), validation (20%, 1685 images), and test sets (10%, 843 images). Data augmentation techniques including random rotation, brightness adjustment, and Gaussian noise injection were applied to enhance model robustness and prevent.

Training Settings: The training image size is 640×640, the batch size is 16, and the number of training rounds is 300;

Environment configuration: PyTorch 2.5.1 framework is adopted, CUDA 12.4 acceleration environment, and the hardware platform is NVIDIA RTX 4090 graphics card;

Evaluation indicators: mAP@0.5 (average accuracy), Precision (accuracy), Recall (recall) are used as performance indicators.

Fig. 3. An example of the open fire image data set.

3.2. Training Process

This section details the specific implementation steps of the model training process. First, we created a new yolov5s_SE.yaml in the yolov5_models folder and copy yolov5s.yaml into the yolov5s_SE.yaml. Second, add SE attention to the previous layer of the SPPF (Fig. 4), and modify the from parameters for both Detect and Concat. Then the attention mechanism code is then put into the yolov5/models/common.py and the next step is to add SE into yolov5/models/yolo.py (as illustrated in Fig. 5). Finally, we modified the cfg parameter in train.py to specify the yolov5s_SE.yaml configuration file (see Fig. 6) and initiated the model training [14].

```
nc: 80 # number of classes
depth_multiple: 0.33 # model depth multiple
width_multiple: 0.50 # layer channel multiple
anchors:
  - [10, 13, 16, 30, 33, 23] # P3/8
  - [30, 61, 62, 45, 59, 119] # P4/16
  - [116, 90, 156, 198, 373, 326] # P5/32

# YOLOv5 v6.0 backbone
backbone:
  # [from, number, module, args]
  [
    [-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
    [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
    [-1, 3, C3, [128]],
    [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
    [-1, 6, C3, [256]],
    [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
    [-1, 9, C3, [512]],
    [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
    [-1, 3, C3, [1024]],
    [-1, 1, SE, [1024]],
    [-1, 1, SPPF, [1024, 5]], # 9
  ]
```

Fig. 4. YOLOv5s architecture diagram with SE attention integrated in the upper layer of SPPF and adjusted connections of Detect and Concat.

```
class SE(nn.Module):
    def __init__(self, c1, c2, ratio=16):
        super(SE, self).__init__()
        # c*1*1
        self.avgpool = nn.AdaptiveAvgPool2d(1)
        self.l1 = nn.Linear(c1, c1 // ratio, bias=False)
        self.relu = nn.ReLU(inplace=True)
        self.l2 = nn.Linear(c1 // ratio, c1, bias=False)
        self.sig = nn.Sigmoid()

    def forward(self, x):
        b, c, _, _ = x.size()
        y = self.avgpool(x).view(b, c)
        y = self.l1(y)
        y = self.relu(y)
        y = self.l2(y)
        y = self.sig(y)
        y = y.view(b, c, 1, 1)
        return x * y.expand_as(x)
```

Fig. 5. YOLOv5 file structure diagram with attention mechanism code incorporated into common.py.

```
n = n_ = max(round(n * gd), 1) if n > 1 else n  # depth gain
if m in {
    Conv,
    GhostConv,
    Bottleneck,
    GhostBottleneck,
    SPP,
    SPPF,
    DWConv,
    MixConv2d,
    Focus,
    CrossConv,
    BottleneckCSP,
    C3,
    C3TR,
    C3SPP,
    C3Ghost,
    nn.ConvTranspose2d,
    DWConvTranspose2d,
    C3x,
    SE,
}:
```

Fig. 6. The YOLOv5 architecture diagram with squeeze-and-excitation module.

3.3. Experimental Results and Model Comparison Summary

To validate the effectiveness of the proposed YOLOv5 fire detection model incorporating the SE attention mechanism, we conducted training and testing on a self-built image dataset containing both flame and smoke targets. The resulting F1-confidence curve chart demonstrates the model's F1-score variation trends across different confidence thresholds, which serves as an evaluation metric for assessing the detector's balanced performance between precision and recall rates.

As shown in the Fig. 7, when the confidence threshold was approximately 0.293, the model achieved the highest F1 value of 0.85 across all categories, indicating that this threshold optimizes detection performance. In single-category analysis, the "smoke" category demonstrated slightly better overall detection performance compared to the "fire" category, particularly showing higher robustness in the medium-low confidence range. This suggests that the introduction of the SE module enhances the model's focus on smoke target features in complex backgrounds, resulting in more comprehensive feature representation.

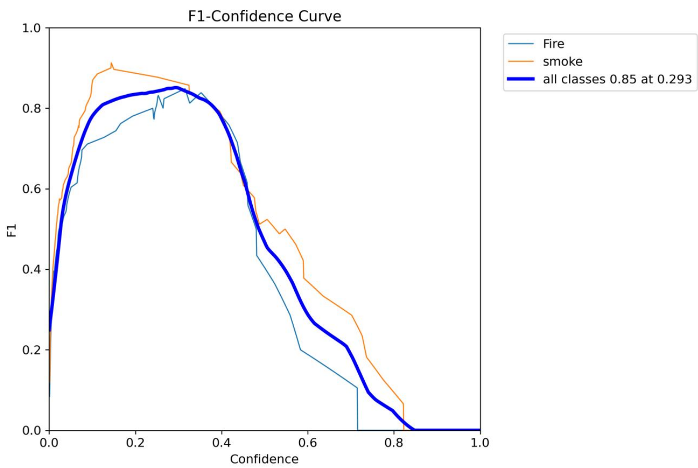

Fig. 7. YOLOv5(with SE)'s F1-confidence curve showing optimal threshold at 0.293 with maximum F1 = 0.85.

Fig. 8 showcases that at a confidence threshold of approximately 0.193, the YOLOv5 (without SE attention mechanism) model achieves the highest F1-score of 0.89 across all classes, indicating its optimal balanced performance at this threshold, with comparable detection performance between the "smoke" and "fire" classes. However, in practical fire detection scenarios, the early warning capability for smoke is often more critical than a high overall F1-score, as smoke typically precedes visible flames and allows for earlier intervention. Therefore, from an application perspective, a model configuration that prioritizes the recall of smoke detection might be more valuable, even if it comes at the cost of a slight decrease in the overall F1-score.

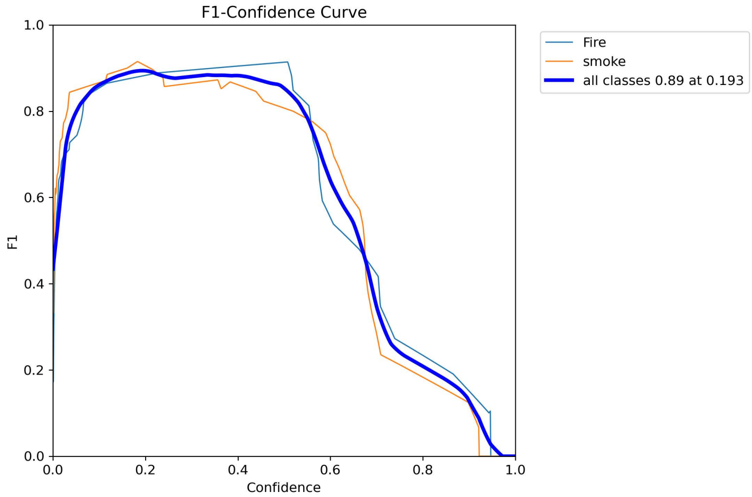

Fig. 8. YOLOv5(without SE)'s F1-confidence curve showing optimal threshold at 0.193 with maximum F1 = 0.89.

Among the YOLO series, YOLOv5(with SE) strikes an optimal balance between detection accuracy and computational efficiency. Fig. 9 has demonstrated that while YOLOv8 achieves slightly high F1-score with 0.85 in some scenarios, YOLOv5 maintains superior F1-score, which outweighs YOLOv8, making it more suitable for real-time applications. This performance characteristic positions YOLOv5 as an ideal baseline for fire detection systems requiring both accuracy and real-time performance.

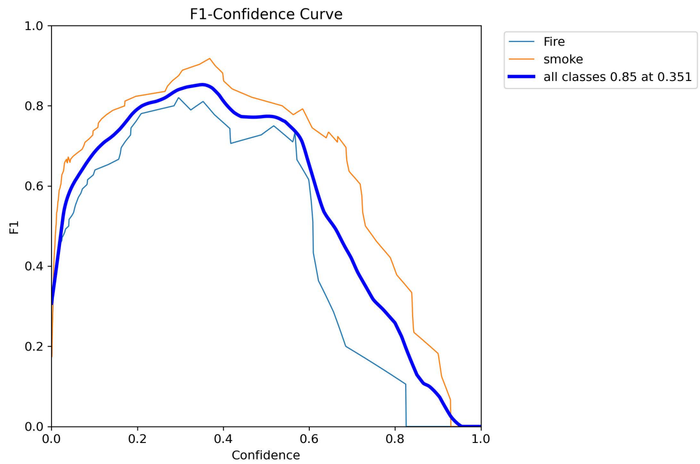

Fig. 9. YOLOv8(without SE)' s F1-confidence curve showing optimal threshold at 0.351 with maximum F1 = 0.85.

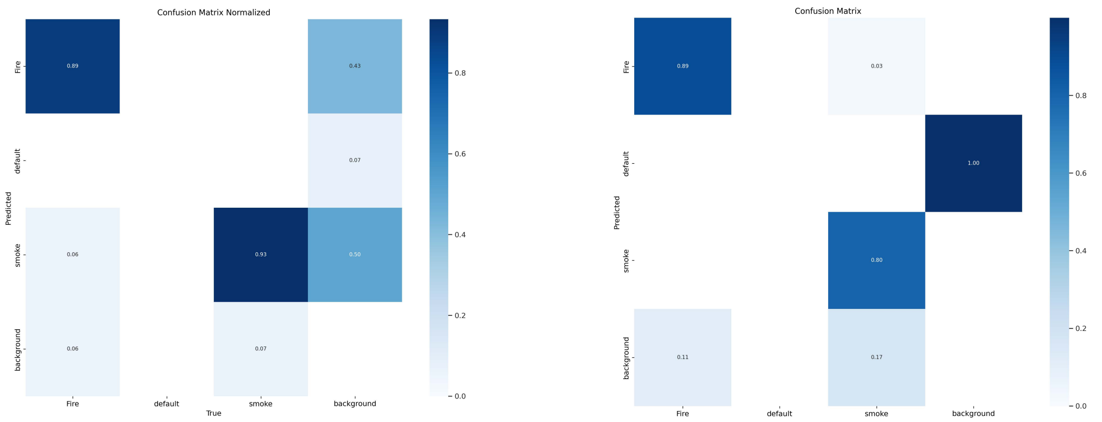

Fig. 10. A comparison between YOLOv8(without SE)'s confusion matrix and YOLOv5(with SE)'s confusion matrix.

Summary: To comprehensively evaluate the effectiveness of the proposed YOLOv5+SE model, we compared its performance against the baseline YOLOv5 and the more recent YOLOv8 model. As illustrated in the F1-confidence curves (Figs. 7–9), YOLOv5+SE achieves a maximum F1-score of 0.85 at a confidence threshold of 0.293, while the baseline YOLOv5 attains a slightly higher F1-score of 0.89 at a lower threshold of 0.193 and the baseline YOLOv8 attains a same F1-score of 0.85 at a higher threshold of 0.351. However, the improved model demonstrates superior smoke detection recall in the medium-to-low confidence range, which is critical for early fire warning.

The confusion matrices (Fig. 10) further confirm that YOLOv5+SE exhibits better generalization and fewer misclassifications in complex fire scenarios. Although YOLOv8 shows competitive performance in some metrics, YOLOv5+SE strikes a better balance between accuracy and real-time inference efficiency (as is shown in Fig. 11), making it more suitable for practical deployment.

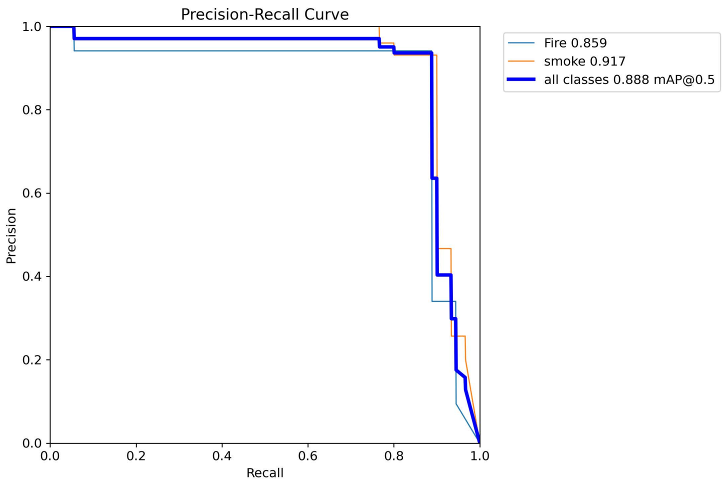

Fig. 11. YOLOv5(with SE)'s Precision and recall are mutually exclusive, with mAP@0.5 of 0.888.

To further verify the stability and optimization effect of the improved YOLOv5 model training, this paper observes the variation of the loss function (Loss) and the evolution of performance indicators (Precision, Recall, mAP) during the training process [15–16].

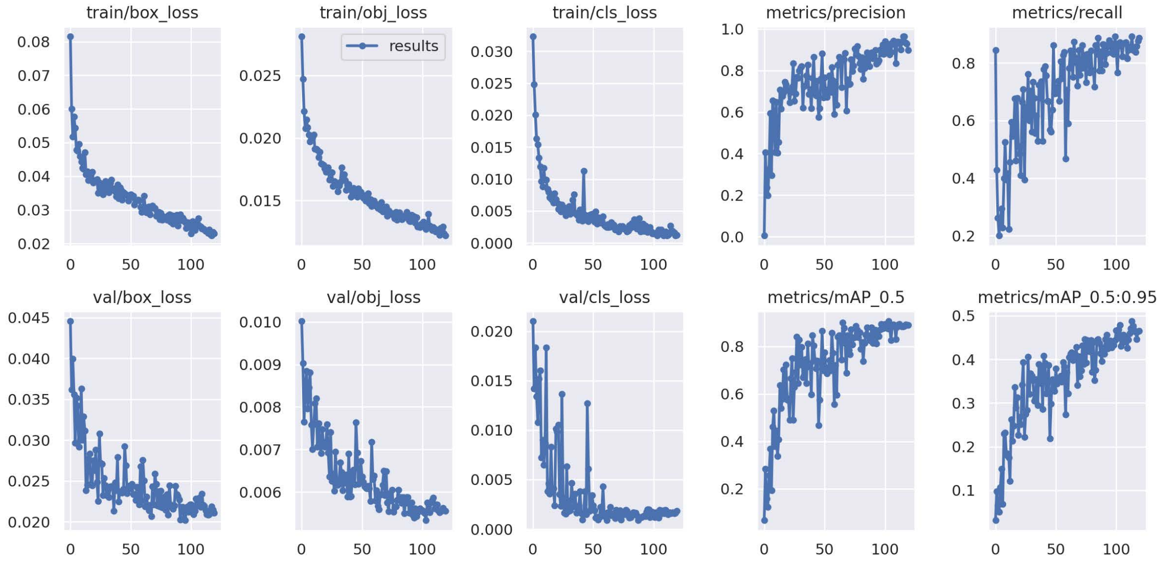

Fig. 12. YOLOv5(without SE)'s evolution curves of loss function and performance metrics during training.

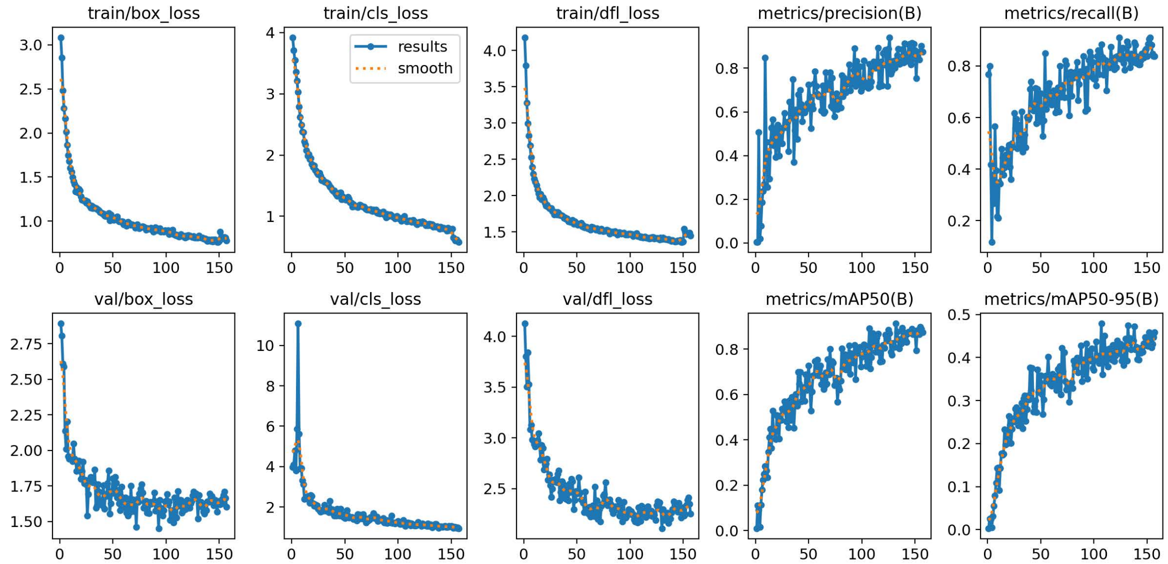

Fig. 13. YOLOv8(without SE)' s evolution curves of loss function and performance metrics during training.

To comprehensively evaluate the performance of the baseline models, this study compared YOLOv5 and YOLOv8 (both without the SE attention mechanism) on the same dataset. As shown in Figs. 12 and 13, both models demonstrated good convergence during training, with their loss functions decreasing and stabilizing. The final validation losses for YOLOv5 stabilized at a box loss of 0.021117, with object loss and class loss converging to 0.0055487 and near zero, respectively. In contrast, YOLOv8's final validation box loss stabilized at 1.6021, with object loss and class loss converging to 0.93977 and 2.2492, respectively [17].

The two models exhibited distinct advantages in different key metrics: YOLOv8 achieved a slightly higher peak accuracy under the relaxed threshold (mAP@0.5: 0.913 vs. 0.906), while YOLOv5 performed better under the more stringent evaluation criterion (mAP@0.5:0.95: 0.487 vs. 0.479), indicating superior performance at higher Intersection over Union (IoU) thresholds and more precise localization. More importantly, significant differences were observed in their training characteristics: YOLOv5 demonstrated faster convergence speed and superior training stability, with smoothly descending loss curves that stabilized rapidly. In comparison, YOLOv8's training process showed considerable fluctuations and required longer cycles to reach optimal performance, which might affect reliability in practical deployment. Considering both convergence efficiency and stability, YOLOv5, as a more mature architecture, provides a more reliable baseline model for integrating attention mechanisms. This capability is crucial for further enhancing smoke detection recall rates, which is vital for early fire warning systems, and establishes a solid foundation for the significant improvements in accuracy and robustness subsequently achieved by the YOLOv5+SE model.

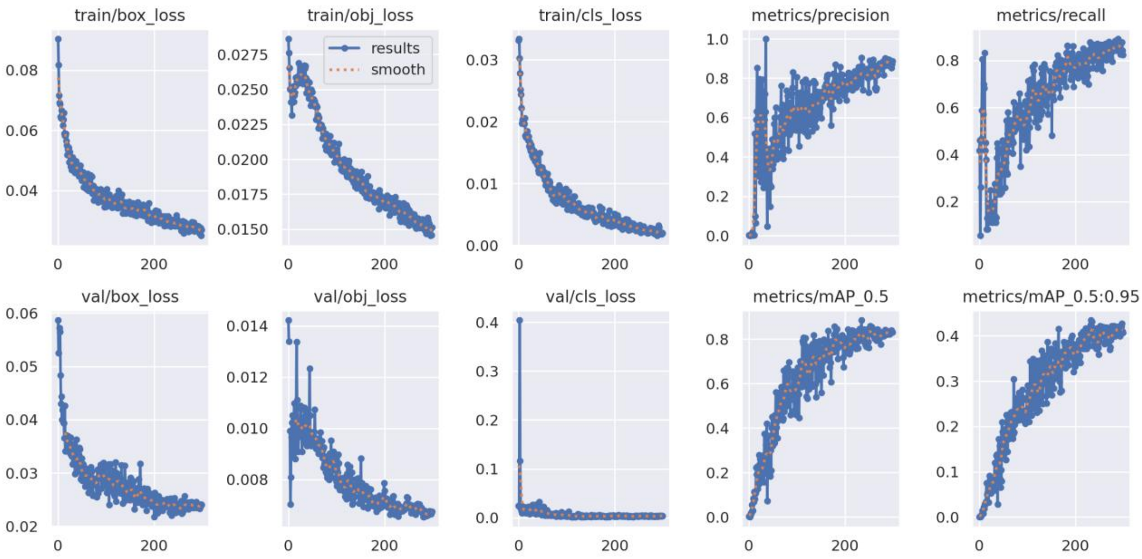

Fig. 14. YOLOv5(with SE)'s evolution curves of loss function and performance metrics during training.

During the model training process, as is shown in Fig. 14, YOLOv5-SE demonstrated excellent convergence and stability. Analysis of loss curves from both training and validation sets revealed a clear downward trend in all metrics—boundary box loss (box loss), object loss (obj loss), and class loss (cls loss)—which stabilized after approximately 200 epochs. The box loss stabilized at around 0.025 in the validation set, while object loss and class loss converged to 0.008 and nearly zero respectively. These results indicate the model's strong performance in target localization, foreground-background classification, and flame/smoke detection tasks. Additionally, Precision and Recall curves showed continuous improvement during training, with optimal values exceeding 0.85 and 0.86 respectively, validating the effective enhancement capability of the SE module in allocating feature channel weights.

Further analysis of mAP metrics reveals that YOLOv5-SE achieves a peak value of 0.91 at mAP@0.5, maintaining a consistent level of 0.42 under the stricter mAP@0.5:0.95 threshold. This demonstrates the model's enhanced robustness not only in handling relaxed IOU thresholds but also in scenarios requiring precise detection box localization. The F1-confidence and Precision-confidence curves highlight optimal performance within the moderate confidence range (approximately 0.29–0.57), effectively mitigating false positives from low confidence and missed detection from high confidence. Comprehensive evaluation indicates that the model achieves three key optimization objectives in fire detection tasks: high precision, stability, and rapid convergence.

It can be seen that the improved YOLOv5 model has significantly improved detection accuracy and recall rate, with a high mAP value, and good Precision and Recall respectively. While this study acknowledges the importance of Frames-Per-Second (FPS) metrics for evaluating real-time performance, specific FPS comparisons were not conducted due to hardware limitations in video processing equipment [18]. However, theoretical analysis suggests minimal impact on inference speed. The SE module introduces only marginal computational overhead, increasing parameters by approximately 1.5%. Future work will include comprehensive FPS benchmarking to fully characterize the model's real-time capabilities across different hardware platforms [19].

From the perspective of actual detection effect, the model with SE attention mechanism has relatively stable performance in processing complex backgrounds (such as street lighting, building reflection, smoke occlusion, etc.), with clear detection results and accurate positioning.

4. Conclusion

This paper addresses fire image detection challenges by introducing a SE attention mechanism into the YOLOv5 network architecture, aiming to enhance the model's capability in recognizing flame target features. By integrating SE modules into both the backbone and neck layers, the improved model outperforms the original YOLOv5 across multiple evaluation metrics, demonstrating significant advantages in detection accuracy and robustness. Experimental validation confirms the method's effectiveness and practicality, providing technical support for deploying intelligent fire monitoring systems.

In the future work, we can further optimize this system from the following directions [20–24]:

Lightweight network structure: consider combining lightweight models such as MobileNet and ShuffleNet to further compress model parameters and improve deployment efficiency;

Multimodal information fusion: combine infrared image, thermal imaging and other sensor information to improve the detection ability of the model in smoke, night and other complex environment;

Data set expansion and enhancement: build a larger scale and more diverse fire image data set, and use GAN and other methods to enhance the data and improve the generalization ability of the model;

Edge computing deployment: Combined with edge computing platforms such as Jetson Nano and Raspberry PI, the optimized model can achieve low power consumption, low latency and full-scenario application on devices with limited resources.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Ruoxi Huang designed the overall research framework, formulated the target detection experiment scheme, conducted model training and validation experiments; Yiming Chen collected the original dataset, assisted in literature review and reference collation for target detection-related studies, and conducted preliminary data verification; Xiasheng Lu performed in-depth data analysis, structured the manuscript, and revised the paper based on peer review comments; all authors discussed the research ideas, reviewed the manuscript, and approved the final version for submission.

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