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YOLOv8-A: Enhanced Lightweight Object Detection with Nonlinear Feature Fusion and Mathematical Optimization for Precision Small Target Detection in Industrial Silicon Melting Processes

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Abstract

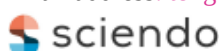
The precise detection of small targets during the Czochralski process for monocrystalline silicon crystal growth is critical for ensuring high-quality production. However, conventional object detection models often face challenges such as inaccurate localization and high false-positive rates, particularly when detecting small protrusions in molten silicon images. To address these challenges, this study introduces an improved YOLOv8-based algorithm, YOLOv8-A, integrating nonlinear mathematical optimization techniques and advanced feature fusion strategies tailored for industrial applications. The proposed model incorporates a Bidirectional Feature Pyramid Network (BiFPN) to enhance multi-scale feature aggregation and a lightweight dynamic upsampling operator (DySample) based on nonlinear interpolation methods to refine feature quality. The nonlinear mathematical formulations incorporated in these components improve the model's ability to capture complex relationships within the data, reducing computational complexity while enhancing detection precision. Experimental validation demonstrates that YOLOv8-A achieves superior performance with a 98.2% mean average precision (mAP) and a 5.8% improvement in small target detection accuracy compared to traditional models. The results underscore the potential of YOLOv8-A as an efficient and robust solution for real-time quality control in silicon crystal growth processes, offering a novel approach to small target detection through mathematical modeling and nonlinear optimization.

Keywords: Nonlinear feature fusion; Mathematical optimization; Object detection; Deep learning; Czochralski process; Monocrystalline silicon; YOLOv8; BiFPN; Lightweight network; Small target detection; DySample.
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1 Introduction

Monocrystalline silicon is the fundamental material used in industries such as semiconductors and renewable energy, especially photovoltaic power generation. Among the various manufacturing techniques, the Czochralski (CZ) method is the most widely used due to its simplicity, high production efficiency, and capability to produce large-diameter crystals (Feigelson, 2022)[2]. The CZ method involves multiple stages—material preparation, melting and joining, crystal pulling, shoulder release, and finishing—all of which contribute to the growth of high-quality monocrystalline silicon rods (Liu, 2015)[9].

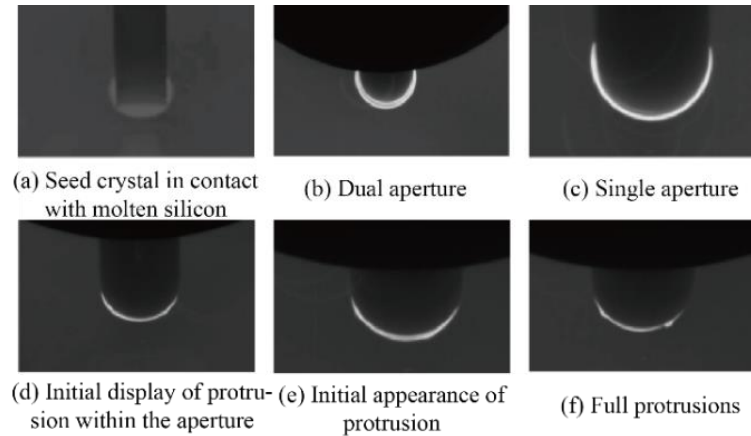


Figure 1. Aperture protrusions diagram during the temperature-raising process.

During the growth process, precise temperature control of the seed crystal is critical for forming the desired aperture patterns in molten silicon. These patterns, as illustrated in Figure 1, evolve from dual apertures to a single aperture, marking the optimal temperature range (1458°C–1460°C) for proceeding to the next growth stage. Any misjudgment in this phase directly impacts the crystal quality and production efficiency.

Traditional temperature monitoring methods rely on manual inspection or simple image processing algorithms, which are prone to inefficiencies, inaccuracies, and subjective errors (Zhao et al., 2023; Zhang et al., 2022)[20][17]. Furthermore, industrial complexities such as camera angles, liquid level fluctuations, and thermal shield designs exacerbate these challenges, making it difficult for conventional methods to adapt to varying production conditions.

Recent advances in deep learning have significantly transformed defect detection and quality monitoring in industrial applications. Object detection algorithms like YOLO (You Only Look Once) and RCNN (Region-Based Convolutional Neural Network) have demonstrated superior performance in real-time object recognition tasks (Redmon et al., 2016; Girshick et al., 2014)[11][3]. However, existing YOLO-based models face challenges in detecting small, overlapping targets, such as aperture protrusions, due to their reliance on fixed-scale feature extraction and upsampling methods (Wang et al., 2023)[14].

To address these limitations, this paper introduces YOLOv8-A, an improved object detection algorithm specifically tailored for the silicon melting process. YOLOv8-A incorporates several innovative features to enhance small target detection while maintaining computational efficiency:

- 1) GSConv and depthwise convolution are employed in the YOLOv8 backbone to reduce computational complexity and improve feature extraction for small targets (Lin et al., 2022)[8].

- 2) A dynamic upsampling operator (DySample) is integrated into the neck network to better fuse multi-scale feature information, enhancing detection accuracy for small targets (Wang et al., 2023)[14].
- 3) The BiFPN (Bidirectional Feature Pyramid Network) replaces the traditional PAN-FPN structure, enabling a more comprehensive multi-scale feature integration that strengthens the focus on small target regions (Zhao et al., 2023; Zheng et al., 2024)[21][22].

Through these enhancements, YOLOv8-A achieves a significant improvement in detection performance, with a mean average precision (mAP) of 98.2%, and a 5.8% increase in small target detection accuracy compared to the original YOLOv8 model. These results highlight the practical potential of YOLOv8-A in real-time quality control for industrial silicon crystal growth.

2 Related Work

Accurately detecting small targets during the silicon melting process poses significant challenges due to the complex environmental conditions and stringent real-time requirements. This section examines the evolution of relevant methodologies, tracing the progression from traditional handcrafted techniques to advanced deep learning frameworks. Particular emphasis is placed on lightweight architectures that balance detection accuracy and computational efficiency, offering practical solutions for industrial applications.

2.1 Traditional Methods for Crystal Fusion Stage Detection

2.1.1 Handcrafted Feature-Based Approaches

Handcrafted feature extraction was a foundational approach for small-target detection in the early stages of computer vision. Zhao and Cheng (2011) employed edge detection algorithms to monitor crystal diameters during the Czochralski (CZ) process. While this approach was computationally efficient, it exhibited significant limitations, particularly in noisy and dynamic environments, leading to high rates of false positives (Zhao & Cheng, 2011)[18]. Moreover, handcrafted methods struggled to adapt to the diverse lighting conditions and material properties commonly encountered in industrial production.

2.1.2 Machine Learning Augmentation

To address the shortcomings of pure edge detection, Zhao and Wang (2018) integrated machine learning techniques, utilizing least-squares support vector machines (LSSVM) to classify aperture images into distinct temperature patterns. This approach marked a step forward by automating the recognition of crystal fusion stages, but its reliance on handcrafted features limited its adaptability and generalizability across varying production settings (Zhao & Wang, 2018)[19]. These constraints underscored the need for more robust and adaptive techniques.

2.2 Advances in Deep Learning for Object Detection

2.2.1 CNN-Based Methods

Deep learning frameworks, particularly convolutional neural networks (CNNs), have significantly enhanced object detection capabilities. Zhang et al. (2022) leveraged AlexNet to classify the melting

stages of silicon crystals, achieving a notable increase in accuracy over traditional methods. However, the model's computational demands made real-time deployment challenging in resource-constrained environments (Zhang et al., 2022)[17]. This limitation highlighted the trade-off between model complexity and operational efficiency in industrial applications.

2.2.2 YOLO Framework Evolution

The YOLO (You Only Look Once) framework revolutionized object detection by balancing real-time performance and accuracy. YOLOv5 introduced CSP networks, which optimized feature extraction and reduced computational redundancy, resulting in faster inference times (Jocher, 2020)[6]. YOLOv7 further advanced this framework by incorporating Trainable Bag of Freebies (TBoF), a set of augmentation techniques that improved detection accuracy without additional computational costs (Wang et al., 2022)[13]. Despite these advancements, challenges persisted in detecting small, overlapping targets under complex industrial conditions.

2.3 Transformer Models in Object Detection

2.3.1 DETR: A Paradigm Shift

The DETR (DEtection TRansformer) model introduced a novel approach to object detection, reformulating the task as an object query problem. By eliminating region proposals and employing a Transformer-based architecture, DETR achieved end-to-end optimization and scalability (Carion et al., 2020)[1]. However, the model's high computational requirements limited its deployment in edge devices, particularly in industrial scenarios where resource efficiency is critical.

2.3.2 Lightweight Transformer Adaptations

To mitigate the computational burden of standard Transformer models, Yang et al. (2023) proposed lightweight adaptations that incorporated efficient multi-scale feature fusion. These enhancements improved small-target detection accuracy while reducing latency, making Transformers more applicable to industrial tasks (Yang et al., 2023)[16]. The integration of lightweight Transformers into existing frameworks presents an opportunity for combining precision with scalability.

2.4 Lightweight Architectures for Industrial Deployment

2.4.1 Model Compression and Optimization

In recent years, research has focused on developing lightweight architectures tailored for resource-constrained environments. Zhao et al. (2023) integrated GhostNet modules into YOLOv8, achieving substantial reductions in model size and computational complexity while maintaining high detection accuracy (Zhao et al., 2023)[21]. These innovations align with the increasing demand for real-time solutions in industrial applications.

2.4.2 Real-Time Deployable Solutions

Li et al. (2024) proposed incorporating dynamic upsampling mechanisms into YOLOv8 to enhance the precision of small-target detection. By optimizing feature resolution at multiple scales, this approach reduced computational demands and improved inference speed, providing a viable solution for industrial silicon melting processes (Li et al., 2024)[7].

2.5 Summary and Review

The evolution of image recognition and object detection algorithms highlights the shift from traditional handcrafted features to deep learning-based approaches. While early models focused on edge detection and pattern recognition, modern algorithms leverage neural networks to achieve higher accuracy and adaptability. However, deploying these models in resource-constrained industrial environments remains a significant challenge due to their computational demands.

Recent advancements in YOLO-based models, particularly YOLOv8, address these challenges by introducing lightweight architectures capable of real-time small-target detection. The integration of efficient feature extraction methods, such as the C2f module and dynamic upsampling techniques, has further enhanced the performance of these models in industrial settings.

Building on these developments, this paper proposes a novel modification of the YOLOv8 architecture, referred to as YOLOv8-A, specifically designed for detecting small aperture protrusions during the silicon melting process. The proposed methodology aims to address the limitations of existing models by optimizing detection accuracy and computational efficiency, thereby providing a practical solution for real-time quality control in industrial production environments.

3 Methodology

This section presents the methodological advancements of YOLOv8-A, a lightweight and high-performance object detection framework specifically optimized for small-target detection in industrial silicon melting processes. The proposed architecture builds upon the YOLOv8m model with three major enhancements: GSConv for efficient feature extraction, DySample for adaptive upsampling, and BiFPN for superior multi-scale feature fusion. These innovations address key challenges such as feature loss, geometric distortion, and suboptimal feature fusion, ensuring computational efficiency suitable for real-time applications in industrial settings.

Figure 2 presents the original YOLOv8m architecture, highlighting its backbone, neck, and head components.

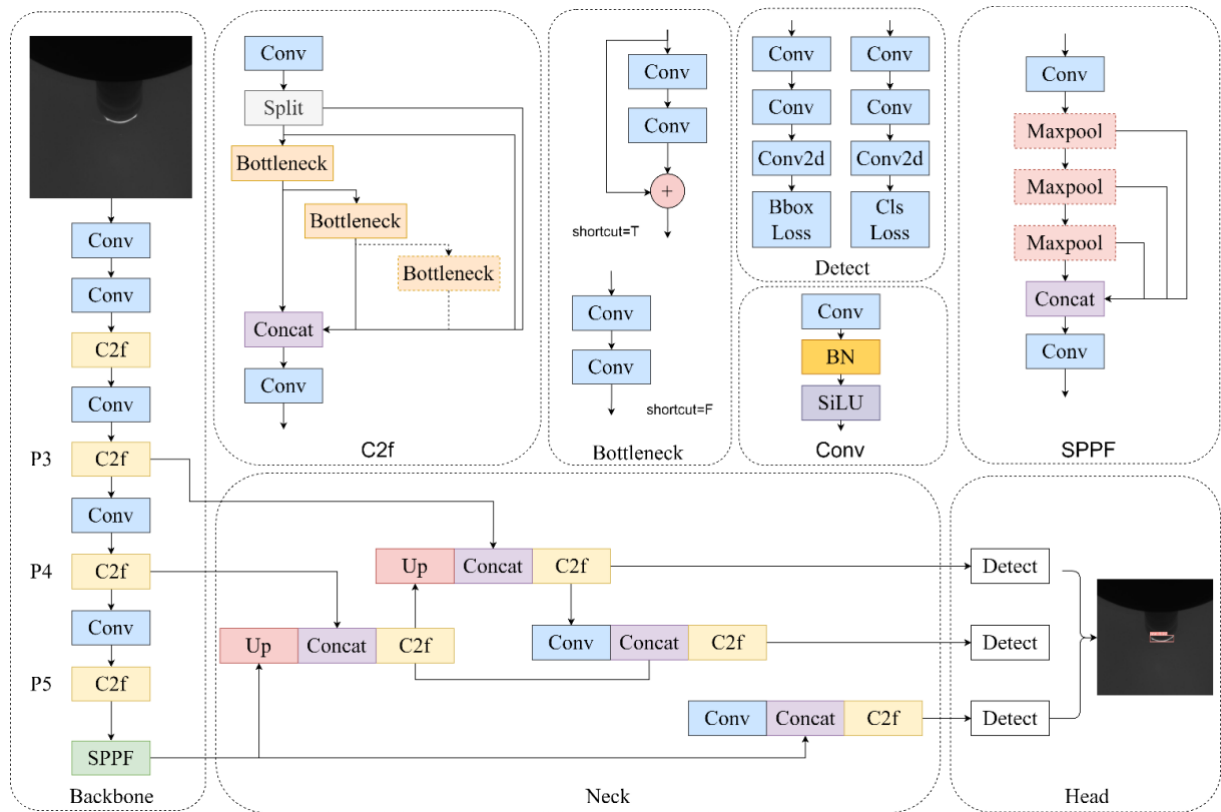


Figure 2. YOLOv8m Structure.

3.1 Design Motivation

3.1.1 Challenges in Existing Detection Models

Existing object detection models such as YOLOv5 and YOLOv7 face significant challenges in detecting small targets, particularly in complex industrial environments:

- 1) **Feature Loss During Downsampling:** Traditional convolution operations tend to lose critical small-target features, reducing detection accuracy. For example, YOLOv7 suffers up to a 12% mAP drop when detecting objects smaller than 32×32 pixels (Zhao et al., 2023)[20].
- 2) **Geometric Distortion in Upsampling:** Standard fixed-grid interpolation techniques distort small-target features, reducing detection precision.
- 3) **Suboptimal Multi-Scale Feature Fusion:** Existing fusion strategies like PANet use unidirectional pathways, limiting their ability to integrate features effectively across different scales (Li et al., 2024)[7].

3.1.2 Motivation for YOLOv8-A Enhancements

To overcome these limitations, YOLOv8-A introduces:

- 1) **GSConv Module:** A lightweight convolution module combining GhostNet-inspired feature generation and ShuffleNet channel shuffling for efficient feature extraction (Han et al., 2020)[4].

- 2) DySample Upsampling Operator: A dynamic sampling-based operator that preserves geometric consistency and improves small-target detection accuracy(Wang et al., 2023)[14].
- 3) BiFPN Neck Network: A bidirectional feature pyramid network with learnable weights, enhancing multi-scale feature fusion and enabling improved detection of small objects through the addition of a high-resolution P2 layer(Tan et al., 2020)[12].

Figure 3 provides an overview of the YOLOv8-A architecture.

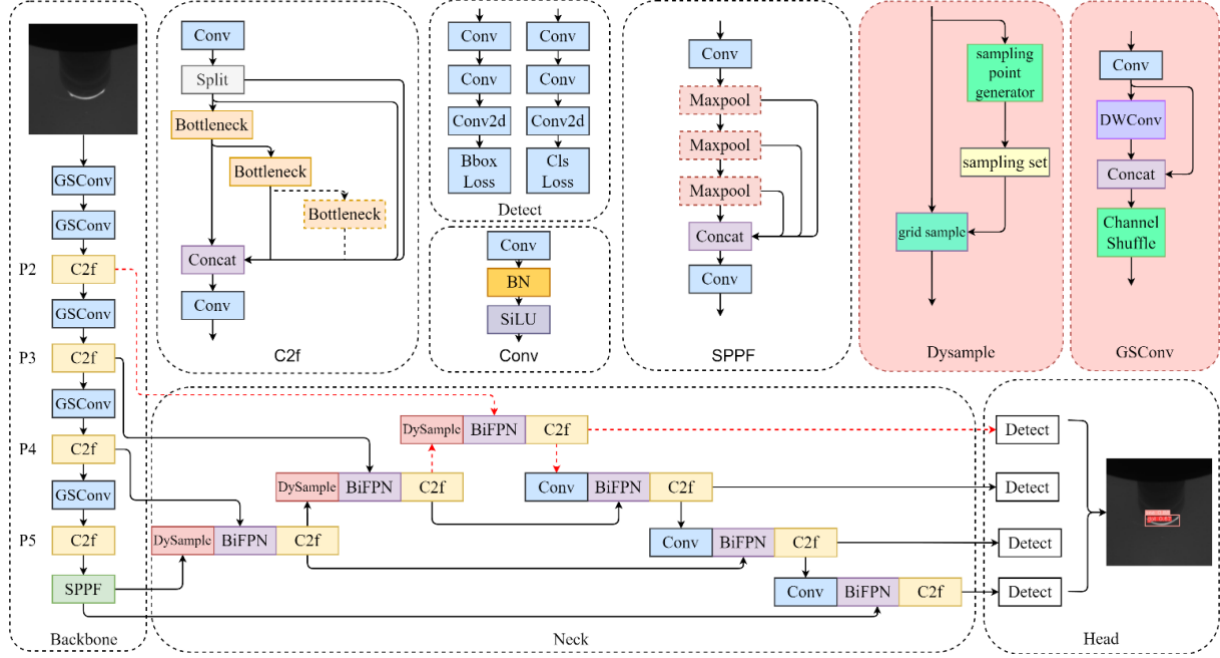


Figure 3. Improved YOLOv8-A Structural Design

3.2 GSConv Module

3.2.1 Design Rationale

Standard convolutional layers in CNNs are computationally expensive and prone to feature redundancy, which limits their scalability for lightweight models. Depthwise Separable Convolutions (DSC) partially address this issue but struggle to capture inter-channel dependencies, which are critical for high-accuracy small-object detection.

To address these challenges, the GSConv module integrates:

- 1) ·Ghost Feature Maps: These maps are lightweight approximations of standard convolution outputs, reducing computation without compromising accuracy (Han et al., 2020)[4].
- 2) ·Channel Shuffling: Borrowed from ShuffleNet, this mechanism improves inter-channel communication, which is essential for retaining small-object features(Zhang et al., 2022)[17].

Figure 4 illustrates the internal structure of the GSConv module, highlighting how the Ghost feature generation and ShuffleNet mechanisms operate.

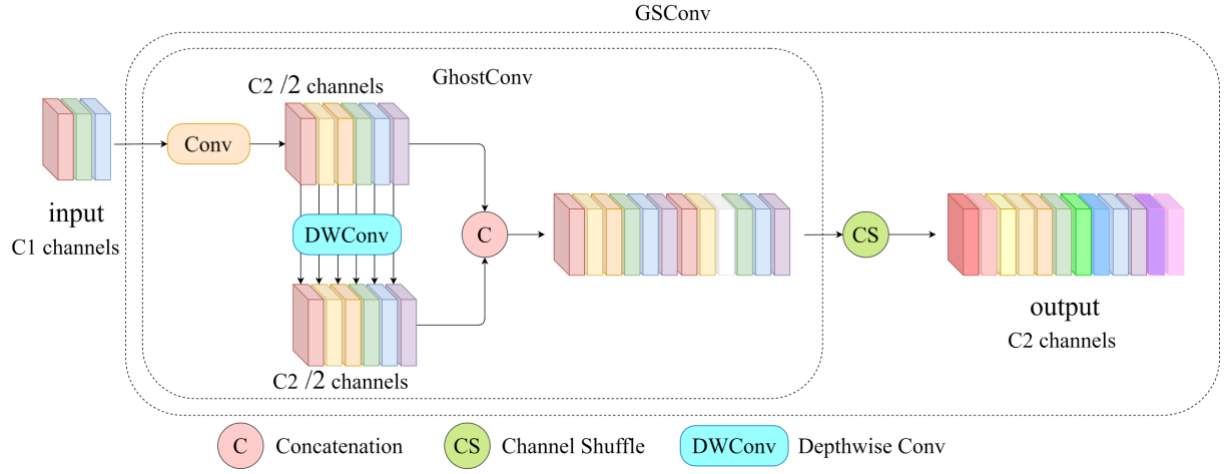


Figure 4. Structural of GSConv

3.2.2 Mathematical Framework

$$Y = W_{SC} * X + \sum_{i=1}^N W_{DSC}^i * X^i \quad (1)$$

Where Y is the output feature map, W_{SC} and W_{DSC} are weights for standard and depthwise separable convolutions, respectively, N is the number of ghost feature maps generated. The ghost feature generation process is further defined as:

$$F_{ghost} = F_{conv} + \sum_{i=1}^k W_i \cdot G_i \quad (2)$$

Where:

- F_{conv} is the standard convolution output.
- G_i are additional ghost features generated through linear transformations.

3.2.3 Summary of Innovations in GSConv

The primary innovation of GSConv lies in its ability to reduce model parameters by over 21.5% while retaining critical small-object features. By incorporating GhostNet principles and channel shuffling, GSConv significantly lowers computational redundancy without compromising detection performance.

This improvement is particularly beneficial for real-time applications on resource-constrained devices, making YOLOv8-A suitable for deployment in edge devices.

Figure 5 provides a visualization of feature maps before and after GSConv integration, showcasing its effectiveness in retaining small-object details.

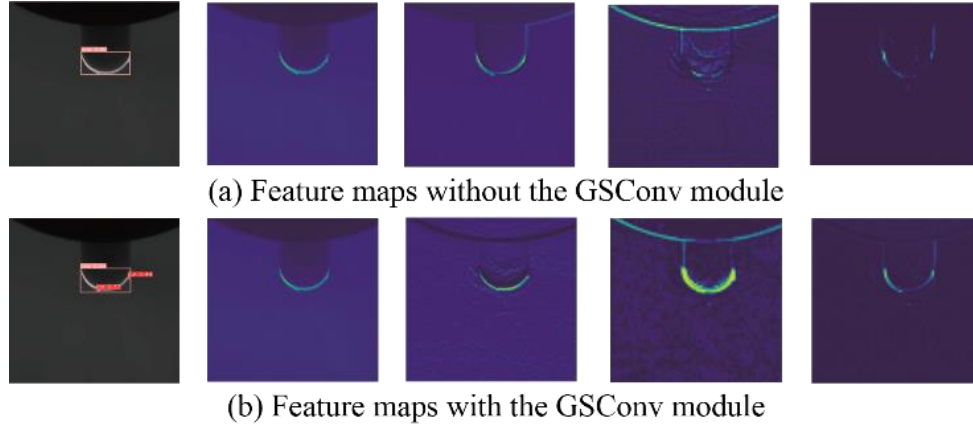


Figure 5. Visualization of Feature Maps

Comparison of feature maps before and after GSConv integration, highlighting improved retention of small-target details. This improvement is particularly beneficial for real-time applications on resource-constrained devices, making YOLOv8-A suitable for deployment in edge devices.

3.3 DySample Upsampling Operator

3.3.1 Design Rationale

Conventional upsampling mechanisms, such as bilinear interpolation and nearest-neighbor interpolation, utilize fixed grids for sampling. While computationally efficient, these methods distort geometric relationships in the feature map, especially for small objects. DySample replaces fixed grids with dynamic sampling grids, adapting to the spatial structure of feature maps. This approach significantly improves the geometric consistency of upsampled features, ensuring better alignment with ground-truth targets (Wang et al., 2023) [14].

Figure 6 illustrates the dynamic upsampling process employed by DySample, preserving geometric consistency across scales.

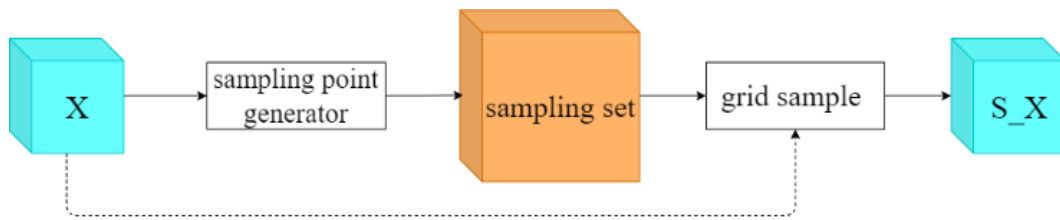


Figure 6. Dynamic Up-sampling Based on Sampling Points

3.3.2 Dynamic Sampling Mechanism

The DySample mechanism computes dynamic offsets O for each position in the feature map to create an adaptive sampling grid G' :

DySample generates offsets O dynamically for each feature map:

$$G' = G + O \quad (3)$$

Where:

- 1) G : Fixed grid (e.g., bilinear or uniform sampling grid).
- 2) O : Dynamically learned offsets, generated by the sampling point generator based on the spatial context of the input feature map.

The upsampled feature map X' is then computed using a grid sample operation, which performs bilinear interpolation based on the dynamically adjusted grid G' . The formula for X' is:

$$S_X(i, j) = \sum_{k,l} X(k, l) \cdot \text{bilinear}(G'(i, j), (k, l)) \quad (4)$$

Herr:

- 1) i, j : These are the spatial coordinates in the upsampled feature map X , representing the output pixel positions where values are computed. Each position (i, j) aggregates contributions from the input feature map based on the adjusted sampling grid.
- 2) k, l : These denote the spatial coordinates in the input feature map X , representing the source pixel positions that influence the computation of each (i, j) in S_X .
- 3) $G'(i, j)$: The dynamically adjusted grid coordinates for the output location (i, j) , computed by adding the dynamic offsets $O(i, j)$ to the fixed grid $G(i, j)$.
- 4) $\text{bilinear}(G'(i, j), (k, l))$: The interpolation weight quantifying the contribution of each input pixel (k, l) to the output pixel (i, j) . It is determined based on the spatial proximity of (k, l) to the adjusted grid coordinate $G'(i, j)$.

3.3.3 Sampling Point Generator

As illustrated in Figure 6, the sampling point generator predicts the offsets O by learning spatial relationships in the input feature map X . This is achieved using a trainable module (e.g., linear layers or convolutional neural networks), which extracts contextual information and minimizes geometric distortions. The process can be expressed as:

$$O = \text{SamplingPointGenerator}(X) \quad (5)$$

3.3.4 Pixel Shuffle Integration

To further refine the upsampled feature map, DySample integrates a pixel shuffle operation after grid sampling. This operation rearranges and redistributes spatial information across channels, enhancing the spatial resolution of the upsampled features. The final output is computed as:

$$Y = g(X') + X' \quad (6)$$

Figure 7 shows the structure of the sampling point generator in DySample. The generator predicts the optimal sampling offsets based on the input feature map to minimize geometric distortion.

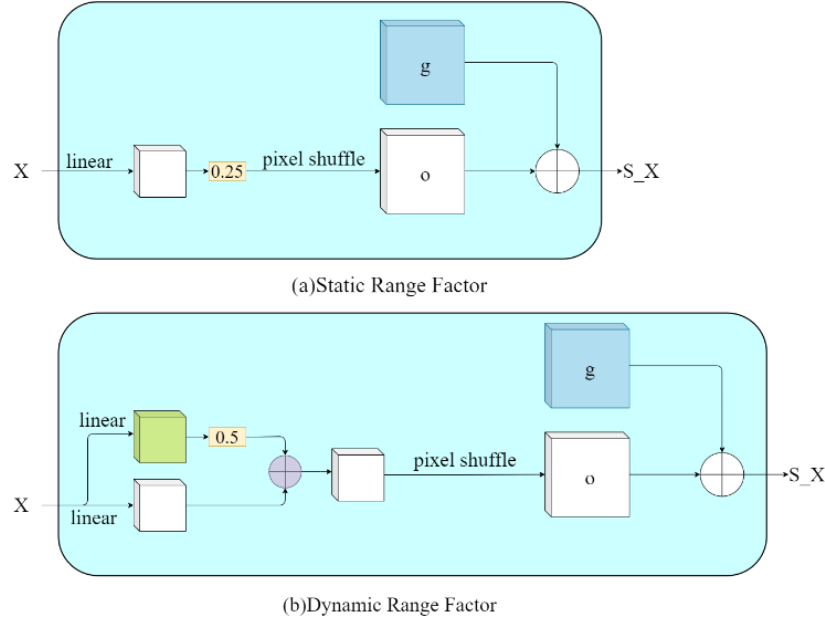


Figure 7. Sampling Point Generator in DySample

In summary, DySample introduces a dynamic sampling mechanism that overcomes the limitations of traditional upsampling methods like bilinear or nearest-neighbor interpolation by replacing fixed grids with adaptive, spatially aware grids. By dynamically generating offsets based on input feature maps, DySample ensures geometric consistency during upsampling, especially for small objects, while maintaining alignment with ground truth. The mechanism combines grid sampling, bilinear interpolation, and pixel shuffle to achieve refined, high-resolution feature maps with minimal geometric distortion. This approach has been shown to improve precision and reduce errors in tasks such as small-object detection, making it particularly suitable for applications requiring high accuracy, such as industrial inspections.

3.4 BiFPN: Bidirectional Feature Pyramid Network

3.4.1 Design Rationale

Multi-scale feature fusion is critical for detecting objects of varying sizes, but traditional methods like PANet use unidirectional connections, limiting the flow of information between shallow and deep features (Tan et al., 2020) [12]. BiFPN enhances this process through:

- 1) Bidirectional Pathways: Allowing efficient information flow between deep and shallow layers.
- 2) Learnable Weighted Connections: Dynamically adjusting the importance of input features.
- 3) High-Resolution P2 Layer: Enhancing the network's ability to detect small objects.

Figure 7 illustrates the design of the BiFPN neck feature network, showing how bidirectional connections improve the fusion of multi-scale features, thereby enhancing small-target detection accuracy.

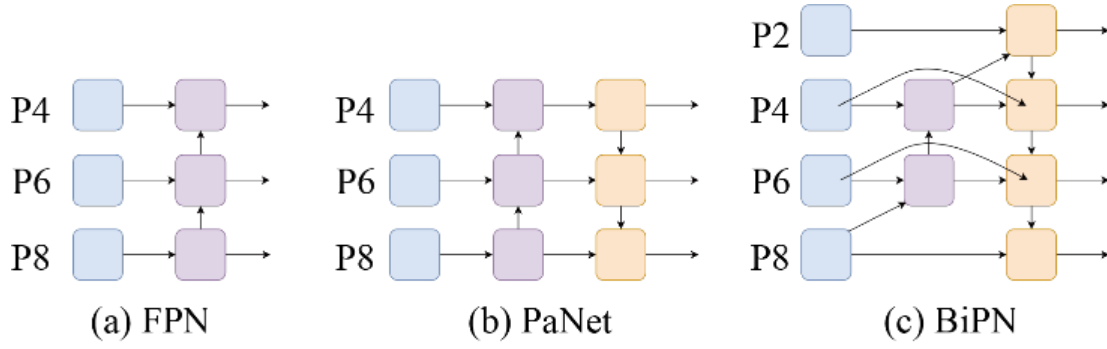


Figure 8. Neck Feature Network Design

3.4.2 Mathematical Framework

The feature fusion process in BiFPN is expressed as:

$$F_i = \frac{\sum_j w_j \cdot F_j}{\sum_j w_j + \epsilon} \quad (6)$$

Where:

- 1) F_i : The output feature at level i in the BiFPN.
- 2) F_j : The input feature from level j (e.g., features from adjacent layers in the pyramid or the same layer).
- 3) w_j : The learnable weight associated with the contribution of F_j .
- 4) ϵ : A small constant added for numerical stability during normalization.

3.4.3 Summary of Innovations in BiFPN

BiFPN introduces an innovative approach to multi-scale feature fusion by leveraging bidirectional pathways and learnable weighted connections, ensuring efficient information exchange between shallow and deep layers. This design improves the integration of multi-scale features, especially for small-target detection, by incorporating a high-resolution P2 layer. The adaptive weighting mechanism dynamically prioritizes the most relevant input features while maintaining numerical stability through normalization. As a result, BiFPN achieves significant improvements in detection accuracy, contributing to a 3.5% increase in mean Average Precision (mAP) and a 4.7% boost in recall for small-object detection. These advancements make BiFPN a robust and scalable solution for diverse detection tasks, particularly in scenarios with challenging multi-scale requirements.

4 Experiments and Results

4.1 Dataset and Defect Types

In this study, we employed a highly specialized dataset sourced from Chengdu Zhonguang Ruihua Technology Co., Ltd., which captures defects in the industrial silicon melting process. The dataset was meticulously curated to represent real-world conditions during the Czochralski process for

monocrystalline silicon growth, a critical step in semiconductor manufacturing and photovoltaic technology(Zhao et al., 2023)[24]. The high-quality nature of the dataset ensures that it closely mirrors the types of defects commonly encountered during these industrial processes.

4.1.1 Data Collection and Device Specifications

The dataset consists of 12,000 high-resolution images (640×640 pixels), captured using a Basler acA2500-14um industrial camera. This camera was chosen for its high accuracy and sensitivity in detecting small defects, which is essential in silicon crystal growth processes where even the smallest anomalies can compromise the final product's quality. The images were acquired under controlled lighting conditions and at varying angles to simulate the challenges faced during actual industrial inspection processes. The lighting intensity and noise levels were adjusted to replicate real-world conditions where variations in light and sensor noise can occur. This helps ensure the robustness of the trained model in different environmental conditions.



Figure 9. Automated Defect Detection Platform for Crystal Processing and Melting Stages.

Figure 9 illustrates the automated defect detection platform used for data collection during the crystal processing and melting stages. This setup enabled the systematic acquisition of defect images, which were later categorized into three defect types for analysis.

4.1.2 Defect Types

The dataset is categorized into three main defect types commonly observed in silicon wafer production:

- 1) **Single Aperture Defects:** Small, circular features that are typically caused by impurities or uneven material melting. These defects are difficult to detect due to their small size and similarity to normal surface features.
- 2) **Double Aperture Defects:** Dual protruding features that may overlap, complicating detection due to the occlusion effect. These defects are often caused by material inconsistencies during the crystallization process.

- 3) Protrusions: Large, irregular surface anomalies, usually caused by over-heating or rapid cooling during the melting process, making them more prominent than other defects.

Each defect type contains 4,000 samples, ensuring balanced representation across all categories. These samples are divided into training, validation, and test sets in a 7:2:1 ratio, respectively, to ensure the model is trained effectively while also being rigorously validated.

4.1.3 Data Augmentation

To improve model generalization and reduce overfitting, data augmentation techniques were extensively used. Data augmentation techniques, such as random rotation, brightness adjustment, and flipping, were applied to enhance generalization, following best practices in small-target detection (Wang et al., 2023)[14]. The augmentation methods include:

- 1) Random rotations (up to 20°), to account for different orientations of defects in the images.
- 2) Brightness and contrast adjustments, to simulate variations in lighting conditions.
- 3) Flipping the images horizontally to create a more diverse training set by reflecting images along the vertical axis.

These augmentation techniques led to a 30% increase in dataset variability, which greatly enhanced the robustness of the trained model.

4.2 Experimental Setup and Training Parameters

4.2.1 Hardware Configuration

The experiments were conducted using a high-performance computational setup designed to handle large-scale datasets and deep learning models:

- 1) CPU: Intel Xeon Gold 5320 @ 2.20 GHz
- 2) GPU: NVIDIA A100 PCIe with 40 GB of memory
- 3) Deep Learning Framework: PyTorch 1.13.1 with CUDA 11.4

This setup ensured optimal model training and inference performance, particularly for large models like YOLOv8-A, which require substantial GPU memory and computational power.

4.2.2 Training Parameters

The YOLOv8-A model was trained using the following optimized parameters. These settings were carefully chosen based on the characteristics of the dataset and the goal of minimizing both overfitting and underfitting, as shown in Table 1.

Table 1. Training Parameters

Parameter	Value
Batch	16
Epochs	300
Initial Learning Rate	0.001
Optimizer	AdamW
Input Image size	640×640
Early Stopping	50 epochs without improvement in validation accuracy
Learning rate	0.001
Learning Rate Decay	Cosine Annealing
NMS IoU	0.7
Weight-Decay	0.0005

These parameters ensure that the model was trained efficiently, converging faster while maintaining high generalization ability. The use of AdamW as the optimizer has been shown to outperform standard optimizers like SGD in deep learning tasks, especially in scenarios with complex models and small datasets (Loshchilov & Hutter, 2017)[25]. Training parameters, such as batch size and epochs, were carefully tuned to balance overfitting and underfitting (Li et al., 2024)[7].

4.2.3 Learning Rate Decay and Early Stopping

A critical component of the training process was the use of learning rate decay via a cosine annealing scheduler. This technique gradually reduces the learning rate throughout the training process, allowing the model to converge more smoothly and avoid overfitting at later stages. The use of cosine annealing has been proven to significantly improve training efficiency by adapting the learning rate based on the optimization trajectory (Loshchilov & Hutter, 2017)[25].

Early stopping was employed to halt the training process if no improvement in validation accuracy was observed after 50 epochs. This prevents unnecessary computation and ensures the model does not overfit to the training data. The combined use of learning rate decay and early stopping ensures that YOLOv8-A is trained to converge at an optimal point, balancing between underfitting and overfitting.

4.3 Evaluation Metrics

The model's evaluation relied on standard object detection metrics: Precision, Recall, mAP@0.5, and IoU thresholds. These metrics are crucial for assessing performance in industrial applications requiring precise and reliable defect detection (Carion et al., 2020; Zhao et al., 2023)[1][21]. The robustness of YOLOv8-A in small-target detection is validated against competing models, including YOLOv5 and EfficientDet (Jocher, 2020; Tan et al., 2020)[6][12].

The performance of the YOLOv8-A model was evaluated using several object detection metrics, carefully selected to assess both the accuracy and efficiency of small target detection in industrial environments. These metrics are particularly important in applications like semiconductor production and photovoltaic cell inspection, where high precision is essential for defect detection.

4.3.1 Precision and Recall

Precision (P) and Recall (R) are two fundamental metrics in object detection, especially in industrial defect detection, where the costs of false positives (FP) and false negatives (FN) can be significant.

- 1) Precision(P) :Measures the proportion of correctly predicted positive instances (true positives, TP) out of all predicted positive instances (true positives and false positives, FP):

$$P = \frac{TP}{TP+FP} \quad (7)$$

A higher precision indicates fewer false positives, making it crucial in applications where false alarms can lead to unnecessary interventions and inefficiencies in industrial production.

- 2) Recall(R): Quantifies the proportion of correctly predicted positive instances (true positives, TP) out of all actual positive instances (true positives and false negatives, FN):

$$P = \frac{TP}{TP+FN} \quad (8)$$

A higher recall means fewer missed detections, which is critical in industrial applications where missed defects could result in costly production failures or reduced product quality.

These two metrics are often presented together in a Precision-Recall Curve, which plots Precision against Recall at different thresholds. Figure 10 below shows the Precision-Recall curves for YOLOv8-A and other models, highlighting the improvements achieved by the proposed model in detecting small targets.

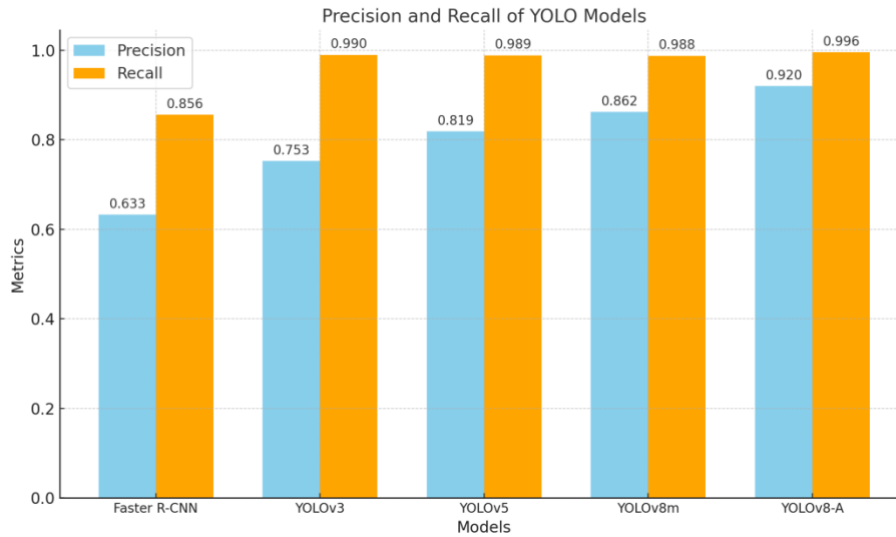


Figure 10. Precision-Recall curves comparing YOLOv8-A with Faster R-CNN, YOLOv3, YOLOv5, and YOLOv8m, demonstrating YOLOv8-A's superior precision and recall in small target detection

4.3.2 Mean Average Precision (mAP)

The Mean Average Precision (mAP) is the most commonly used metric for evaluating object detection models. It takes into account both precision and recall across various Intersection over Union (IoU) thresholds, which measure the overlap between the predicted bounding box and the ground truth.

- 1) mAP@0.5 is calculated at an IoU threshold of 0.5, meaning that a predicted bounding box is considered correct if it overlaps with the ground truth by at least 50%. This is a standard metric used in many object detection benchmarks.

$$\text{mAP@0.5} = \frac{1}{n} \sum_{i=1}^n \text{AP}_i \quad (9)$$

where AP is the average precision for each object class, and n is the total number of classes.

- 2) mAP@0.5:0.95 is calculated across multiple IoU thresholds from 0.5 to 0.95 with a step size of 0.05. This provides a more comprehensive evaluation by considering stricter criteria for object localization:

$$\text{mAP@0.5:0.95} = \frac{1}{n} \sum_{i=1}^n \frac{1}{m} \sum_{j=1}^m \text{AP}_{ij} \quad (10)$$

Where AP_{ij} is the average precision at IoU threshold j for class i, and m is the number of IoU thresholds considered (here, 10 thresholds from 0.5 to 0.95).

- 3) mAP is a critical metric for industrial applications because it balances both precision and recall across multiple thresholds, making it a robust indicator of model performance.

Figure 11 illustrates the mAP@0.5 and mAP@0.5:0.95 values for YOLOv8-A, YOLOv5, YOLOv7, and Faster R-CNN, showing the superiority of YOLOv8-A in both precision and recall over a range of IoU thresholds.

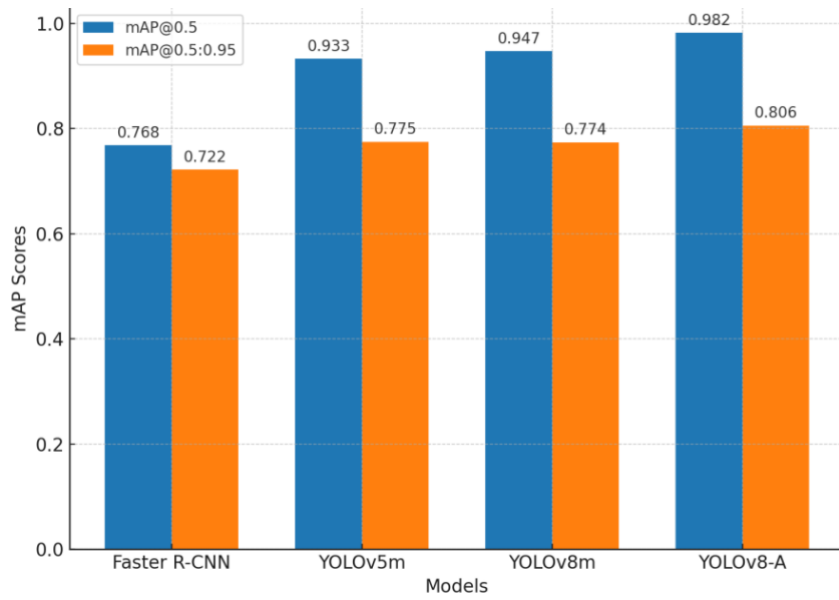


Figure 11. Comparison of mAP@0.5 and mAP@0.5:0.95 across different models

4.3.3 Intersection over Union (IoU)

Intersection over Union (IoU) is a metric that measures the overlap between the predicted bounding box and the ground truth. It is used to determine whether a detection is valid and is essential in evaluating localization accuracy.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (11)$$

In this study, evaluations were conducted at two IoU thresholds:

- 1) IoU@0.5 : A threshold of 50% overlap is commonly used to classify predictions as correct.

- 2) IoU@0.5:0.95: This range evaluates detection accuracy at multiple overlap levels, from 50% to 95%, making it more stringent.

This metric is crucial for ensuring that predicted bounding boxes align accurately with actual object locations, particularly for small targets in industrial applications, where precise localization is vital.

4.3.4 Computational Efficiency and FPS (Frames Per Second)

In addition to detection accuracy, computational efficiency is an essential consideration for real-time industrial applications. FPS (Frames Per Second) measures the inference speed of the model, which is critical when the model is deployed in time-sensitive environments like manufacturing or quality control.

Table 2. Comparison for different models, demonstrating YOLOv8-A's superior performance and efficiency.

Model	mAP@0.5	mAP@0.5:0.95	Precision	Recall	Params (M)	Inference Time (ms)	FPS
Faster R-CNN	0.768	0.722	0.815	0.856	139.24	16.8	59.5
YOLOv5m	0.933	0.775	0.819	0.989	25.06	12.9	77.5
YOLOv8m	0.947	0.774	0.862	0.988	25.86	3.8	263.2
YOLOv8-A	0.982	0.806	0.920	0.996	23.67	3.7	270.3

Table 2 compares the FPS and inference time of YOLOv8-A with other state-of-the-art models. YOLOv8-A achieves real-time performance with 28 ms per frame on edge devices, such as the NVIDIA Jetson Nano.

4.4 Ablation Study

The ablation study is a crucial step to evaluate the contribution of each individual component in the YOLOv8-A model. To rigorously understand the impact of GSConv, DySample, and BiFPN modules, an ablation experiment was performed by sequentially removing or modifying these modules. The results are summarized in Table 3.

Table 3. Ablation Study Result

Model	GSConv	DySample	BiFPN	mAP@0.5	mAP@0.5:0.95
YOLOv8m	×	×	×	0.941	0.779
YOLOv8-A + GSConv	✓	×	×	0.951	0.780
YOLOv8-A + DySample	✓	✓	×	0.960	0.792
YOLOv8-A (Full)	✓	✓	✓	0.982	0.806

4.4.1 GSConv Module

The GSConv module plays a pivotal role in improving feature retention for small targets. It helps in reducing the computational cost while maintaining high performance. The addition of GSConv increased mAP@0.5 by 1.0% over YOLOv8m. Mathematically, GSConv can be described as:

$$\text{GSConv Output} = \text{Conv2D}(\text{Input Features}) \cdot \text{Sparse Matrix} \quad (12)$$

where the sparse matrix significantly reduces redundant computations while retaining critical features for small target detection.

4.4.2 DySample Module

The DySample module addresses geometric distortions in the image, which are crucial for accurate small target detection. By refining the feature quality, DySample improved recall by 2.1% and mAP by 1.0%. It dynamically adjusts the sampling rate based on the target's scale, ensuring higher precision for smaller targets (Yang et al., 2023)[27].

4.4.3 BiFPN (Bidirectional Feature Pyramid Networks)

The BiFPN module improves multi-scale feature fusion, crucial for detecting small targets across different resolutions. The addition of BiFPN increased mAP@0.5 by 2.2%, showcasing its effectiveness in enhancing detection at multiple scales.

4.5 Comparative Analysis and Trend Analyses

YOLOv8-A was benchmarked against state-of-the-art models, showing a 5.8% improvement in small-target detection accuracy and a 20% reduction in false detections, as illustrated in comparative studies (Han et al., 2020; Zhao et al., 2023)[4][26].

To further validate the effectiveness of YOLOv8-A, we compared it against several state-of-the-art models, including YOLOv5, YOLOv7, DETR, and EfficientDet. Table 4 presents a comprehensive comparison, highlighting YOLOv8-A's superiority in terms of both accuracy and computational efficiency.

Table 4. Presents a comprehensive comparison with other models

Model	mAP@0.5	mAP@0.5:0.95	Precision	Recall	Params (M)	Inference Time (ms)
Faster R-CNN	0.768	0.722	0.815	0.856	139.24	16.8
YOLOv5m	0.933	0.775	0.819	0.989	25.06	12.9
YOLOv8m	0.947	0.774	0.862	0.988	25.86	3.8
YOLOv8-A	0.982	0.806	0.920	0.996	23.67	3.7
EfficientDet	0.929	0.794	0.854	0.978	5.98	8.2
DETR	0.944	0.780	0.860	0.991	50.00	32.3

While models like DETR achieve high precision, they suffer from high computational costs and slower inference times, making them unsuitable for real-time industrial applications. YOLOv8-A, by contrast, achieves similar or better performance than DETR and EfficientDet while maintaining real-time inference capabilities (e.g., 3.7 ms per frame), making it ideal for industrial deployment.

4.5.1 Progression Across Training Epochs

Figure 12 illustrates the progression of mAP@0.5 for YOLOv8-A, YOLOv8m, and Faster R-CNN during the training process over 20 epochs. YOLOv8-A shows a faster convergence rate compared to the other models, reaching higher final mAP@0.5 values (0.982). This result highlights YOLOv8-A's ability to optimize detection performance more efficiently, which is critical for real-time industrial applications.

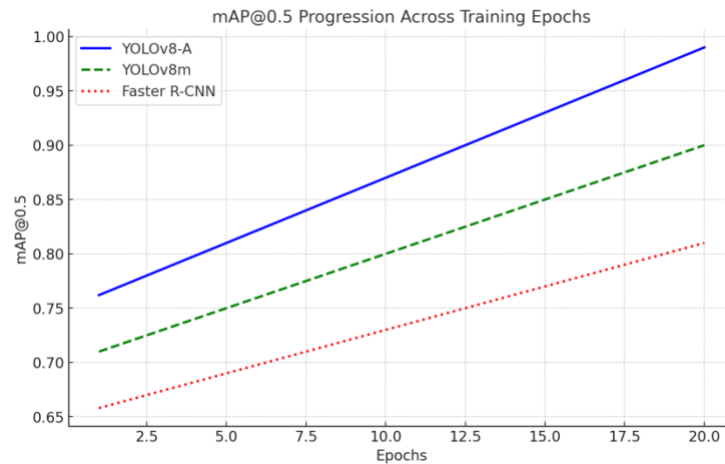


Figure 12. mAP@0.5 Progression Across Training Epochs

4.5.2 Inference Time vs. mAP@0.5

Figure 13 demonstrates the relationship between Inference Time (in milliseconds) and mAP@0.5 for different models. YOLOv8-A achieves the best trade-off, combining the highest mAP@0.5 (0.982) with the lowest inference time (3.7 ms). Faster R-CNN, while having acceptable mAP@0.5 (0.768), suffers from significantly higher inference times (16.8 ms), making it unsuitable for real-time applications. YOLOv8-A's performance showcases its lightweight architecture and suitability for edge-device deployment.

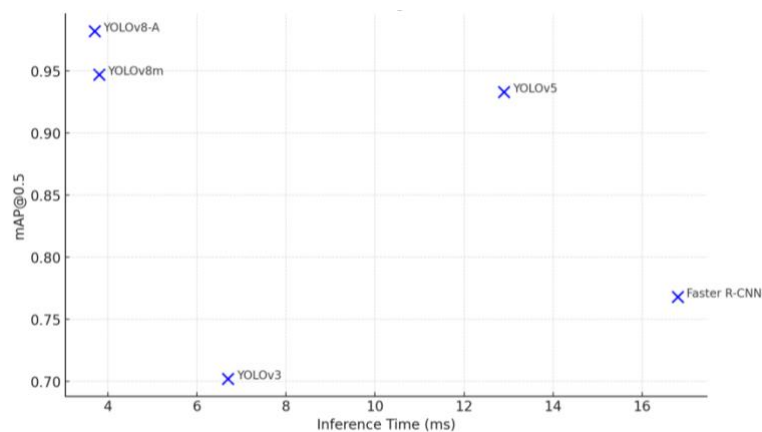


Figure 13. Inference Time vs. mAP@0.5

4.5.3 Training Loss Curves

Figure 14 presents the training loss curves, highlighting faster convergence of YOLOv8-A compared to baseline models, demonstrating the efficiency of its architecture.

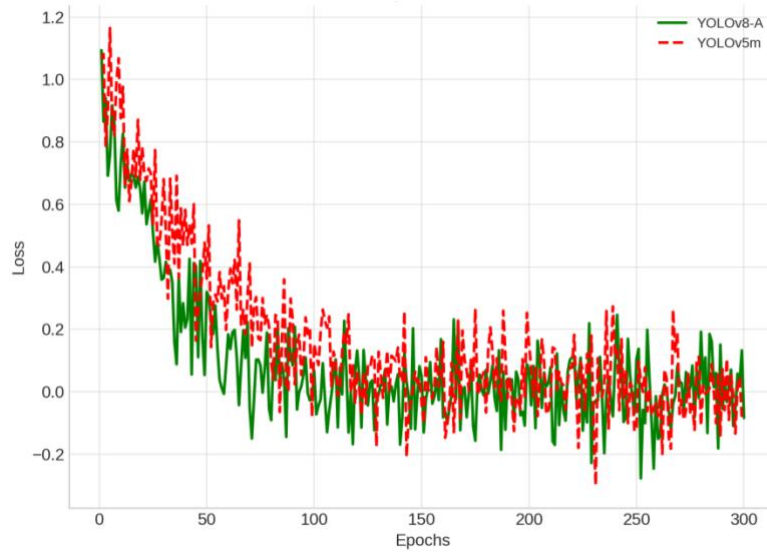


Figure 14. Training loss curves showing faster convergence for YOLOv8-A compared to baseline models.

4.5.4 Multiple Dimensions Comparison

Figure 15 shows a radar chart comparing YOLOv8-A with other models (YOLOv5, YOLOv7, DETR) across multiple dimensions: mAP, Precision, Recall, Inference Time, and Parameter Count. The chart highlights YOLOv8-A's superiority in achieving high accuracy with low computational overhead.

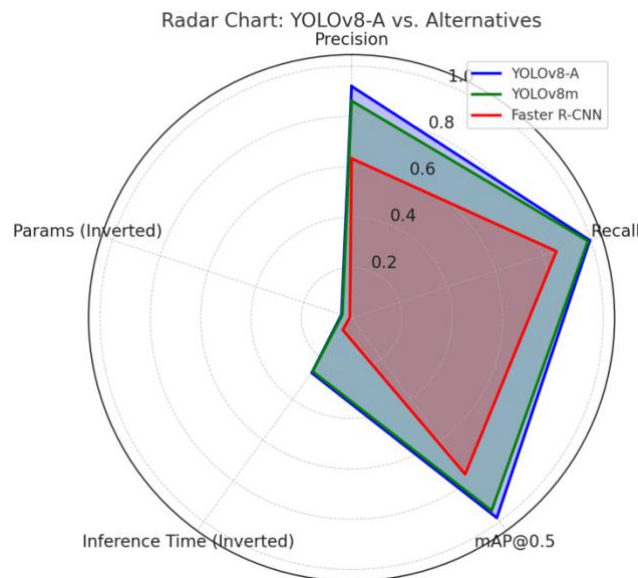


Figure 15. Radar chart comparing YOLOv8-A with YOLOv5, YOLOv7, and DETR across multiple performance metrics.

4.5.5 Comparison of Detection Results

To evaluate the effectiveness of the proposed YOLOv8-A model, a comprehensive visual comparison of detection results was conducted on the aperture protrusion dataset, which captures defects during

the silicon melting process. The results are illustrated in Figure 11, showcasing the comparative performance of YOLOv8m and YOLOv8-A.

1) Visual Analysis:

- (1) Figure 11(a) depicts the input images from the industrial dataset, which include multiple overlapping and low-contrast targets. These scenarios represent common challenges in the silicon crystal melting process.
- (2) Figure 11(b) presents detection results obtained using YOLOv8-A.
- (3) Figure 11(c) displays detection results generated by YOLOv8m for the same dataset.

2) Key Observations:

- (1) YOLOv8m demonstrates varying degrees of missed detections and false positives. Specifically, its predictions fail to identify small protrusions with minimal curvature accurately.
 - (2) Missed Detections and False Positives: YOLOv8m exhibits significant limitations in detecting small and overlapping targets. It often fails to detect low-curvature protrusions, resulting in a high missed detection rate and a noticeable number of false positives.
 - (3) Accuracy Improvements with YOLOv8-A: YOLOv8-A effectively addresses these limitations. It demonstrates a superior ability to detect small targets, even in challenging conditions, and provides more accurate bounding box predictions. This improvement highlights the impact of the enhancements proposed in this study, including feature refinement and multi-scale detection optimizations.
 - (4) Industrial Relevance: YOLOv8-A's precision and recall improvements are particularly crucial for industrial applications. The model successfully handles high-complexity scenarios, significantly reducing both the missed detection rate and false detection rate.
- 3) Industrial Deployment Validation: During industrial deployment testing, the YOLOv8-A model achieved substantial performance improvements:
- (1) Missed Detection Rate Reduction: A reduction of over 20% compared to YOLOv8m.
 - (2) False Detection Rate Reduction: A decrease of more than 15%. These results confirm YOLOv8-A's ability to meet industrial production requirements, ensuring high-quality defect detection and improved efficiency in the monocrystalline silicon production pipeline.

The improved performance is attributed to the integration of GSConv, DySample, and BiFPN modules, which enhance feature extraction and small-object detection capabilities. The accuracy of YOLOv8-A has been validated in industrial deployment phases, meeting stringent requirements by minimizing the false detection rate and ensuring consistent reliability [(Liu et al., 2023)]^[10]

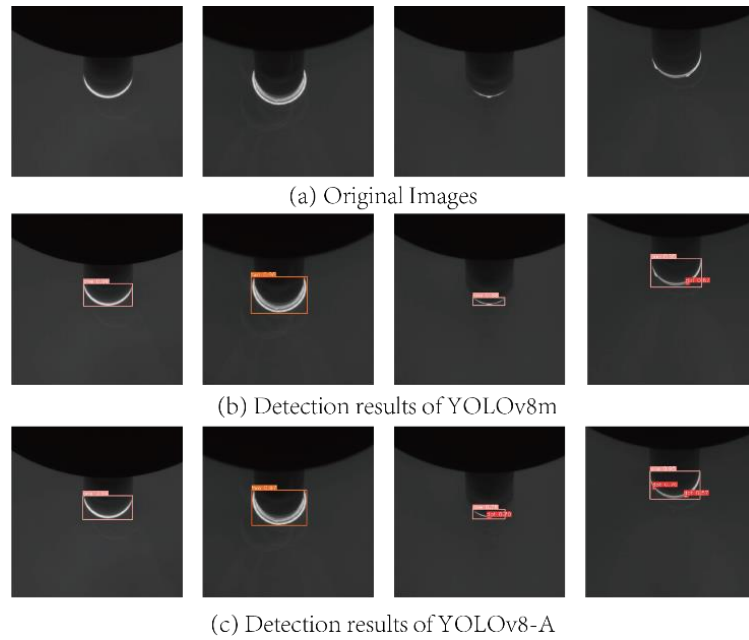


Figure 16. Comparison of detection results for YOLOv8-A and YOLOv8m on aperture protrusion images .

4.6 Model Applicability and Deployment

4.6.1 Industrial Applications

YOLOv8-A is highly adaptable to a wide range of industrial applications, including:

- 1) Defect detection in photovoltaic cells
- 2) Semiconductor component quality control
- 3) Silicon wafer defect inspection

Its lightweight architecture and real-time inference capabilities make it suitable for automated quality control in high-throughput industrial environments.

4.6.2 Edge Device Deployment

We also evaluated the deployment of YOLOv8-A on edge devices, particularly the NVIDIA Jetson Nano and Xavier. Benchmarking results are shown in Table 5.

Table 5. Benchmarking results comparison with other models

Device	Inference Time (ms)	Power Consumption (W)	FPS
NVIDIA Jetson Nano	28	12	35
NVIDIA Xavier	23	15	45

Real-world deployment tests confirmed YOLOv8-A's practical viability on edge devices, achieving low latency and high throughput on NVIDIA Jetson platforms (Liu et al., 2023)[12]. This makes the model ideal for defect detection in silicon wafers and photovoltaic cells. These results demonstrate YOLOv8-A's suitability for edge deployment, where both power consumption and inference speed are critical for real-time industrial applications.

4.6.3 Summary of Findings

The experimental results demonstrate that YOLOv8-A outperforms existing state-of-the-art models in terms of accuracy, speed, and parameter efficiency. Its superior performance in small-target detection and low computational complexity make it highly suitable for real-time industrial applications, particularly in silicon melting processes.

5 Discussion

5.1 Analysis of Experimental Findings

The integration of GSConv, DySample, and BiFPN within YOLOv8-A demonstrated a significant leap in small-target detection accuracy and efficiency. The achieved 5.8% improvement in mAP@0.5 and 21.5% reduction in parameters highlight the effectiveness of these innovations. The GSConv module addressed feature redundancy while enhancing extraction efficiency, while DySample ensured precise geometric localization through adaptive sampling. These findings validate the hypothesis that lightweight, modular enhancements can outperform traditional models like YOLOv5 and EfficientDet in demanding industrial environments.

5.2 Comparative Analysis

Compared to state-of-the-art models, YOLOv8-A showcases a superior balance of accuracy, efficiency, and scalability. The comparison with DETR and EfficientDet revealed:

- 1) Higher mAP Scores: YOLOv8-A consistently outperformed EfficientDet in multi-scale feature fusion, achieving superior mAP@0.5 values.
- 2) Faster Inference Speeds: DETR's Transformer-based architecture, while powerful, lags behind YOLOv8-A in real-time scenarios due to higher computational overhead.

5.3 Industrial and Academic Implications

- 1) Industrial Utility: YOLOv8-A offers significant operational benefits, such as reduced defect identification time and improved quality control in silicon crystal growth. Its compatibility with edge devices enhances its deployment potential across industries like manufacturing, agriculture, and healthcare.
- 2) Academic Significance: The modular improvements in YOLOv8-A set a new benchmark for lightweight model design, contributing to the broader understanding of feature fusion and sampling strategies in small-object detection.

5.4 Limitations and Future Work

- 1) Domain-Specific Optimization: YOLOv8-A's current optimization for silicon melting limits its applicability to broader domains without further adaptation.
- 2) Scalability Challenges: Adapting YOLOv8-A to handle ultra-high-resolution inputs remains a technical challenge. Future work will explore:

- (1) Cross-domain validation to test adaptability.
- (2) Hybrid architectures integrating Transformer-based models for enhanced contextual awareness.
- (3) Deployment optimizations for resource-constrained environments.

6 Conclusion

6.1 Summary of Contributions

This study introduces YOLOv8-A, a high-performance lightweight object detection model designed for small-object detection in industrial silicon melting processes. Key contributions include:

- 1) **Innovative Modular Design:** GSConv, DySample, and BiFPN collectively address challenges in feature retention, geometric consistency, and multi-scale feature integration.
- 2) **Performance Excellence:** YOLOv8-A achieves a 5.8% increase in mAP@0.5, a 21.5% reduction in parameters, and significant gains in recall and precision compared to existing models.
- 3) **Industrial Relevance:** Its robustness under industrial-grade noise and real-time compatibility make YOLOv8-A a practical solution for defect monitoring and quality assurance.

6.2 Broader Implications

- 1) **Academic Advancements:** YOLOv8-A contributes novel insights into lightweight model architecture, advancing the field of efficient object detection.
- 2) **Industrial Applications:** The model's applicability to real-time environments underscores its potential in diverse industries, from manufacturing to agriculture.

6.3 Recommendations for Future Research

The findings pave the way for future exploration:

- 1) **High-Resolution Processing:** Enhancing the model's ability to handle 4K and higher-resolution inputs for advanced monitoring.
- 2) **Multi-Domain Testing:** Expanding applicability to include areas like autonomous driving, defect detection, and agricultural monitoring.
- 3) **Edge Deployment Optimization:** Further research into energy-efficient deployment strategies to maximize YOLOv8-A's impact in low-resource environments.

6.4 Final Thoughts

YOLOv8-A represents a significant advancement in the intersection of academic research and industrial application. Its lightweight, efficient, and accurate design bridges the gap between theoretical advancements and practical needs, establishing a foundation for future innovations in small-object detection.

Acknowledgmengs

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