Benchmarking few-shot learning techniques for steel surface defect detection

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CFRIA — CARREFOUR DE FORMATION EN ROBOTIQUE INDUSTRIELLE ET INTELLIGENCE ARTIFICIELLE

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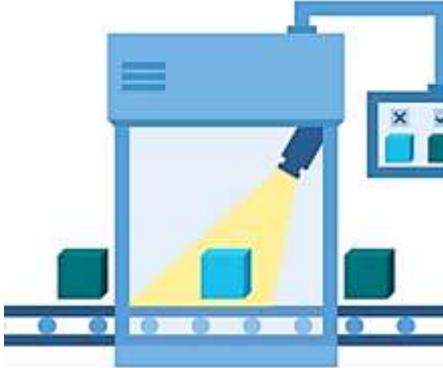- Results & Discussion
- Conclusion
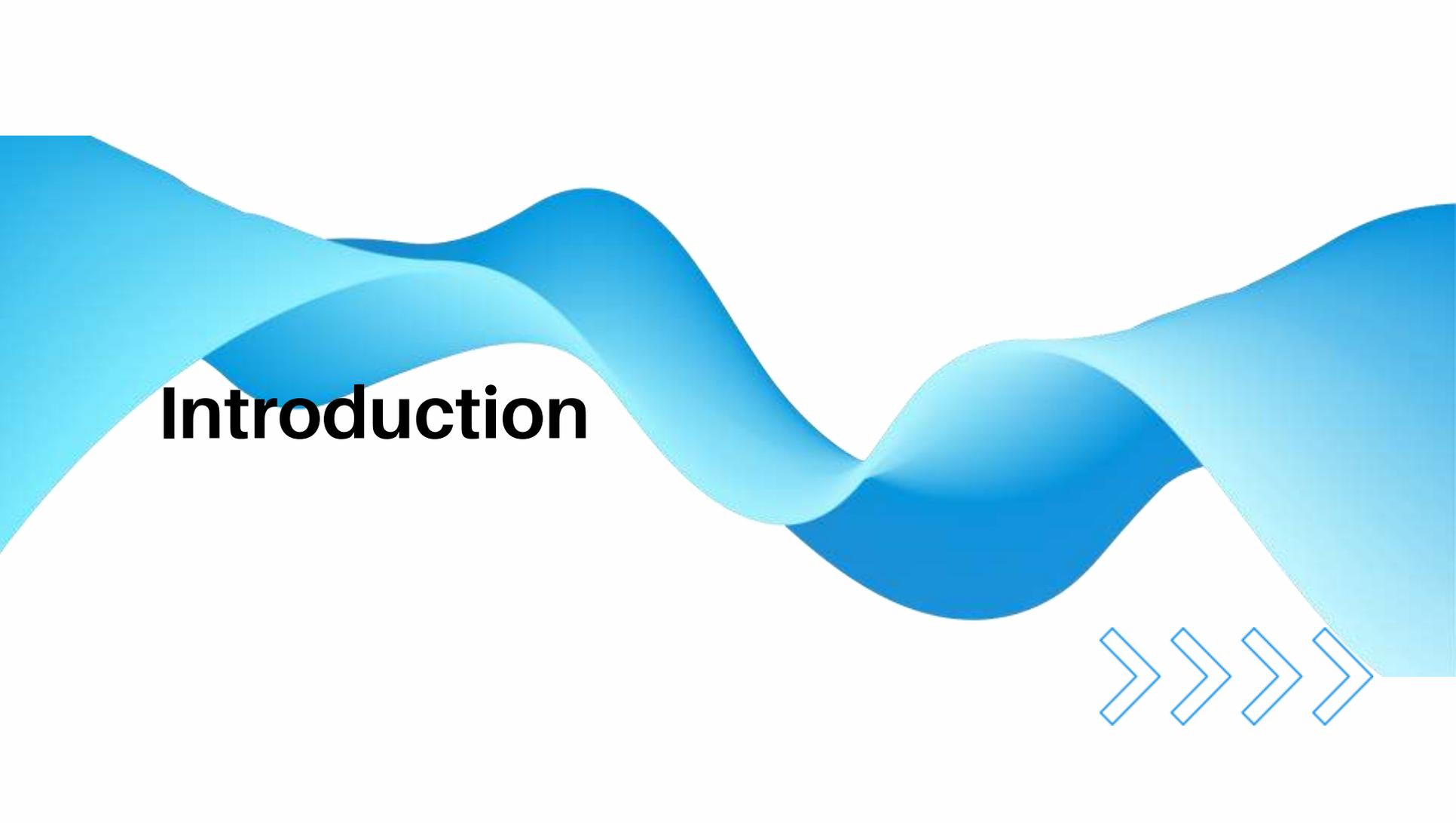
Introduction

Industrial vision applications

Smart manufacturing

Automated quality inspection

Integrating AI into quality inspection

Consistent product quality

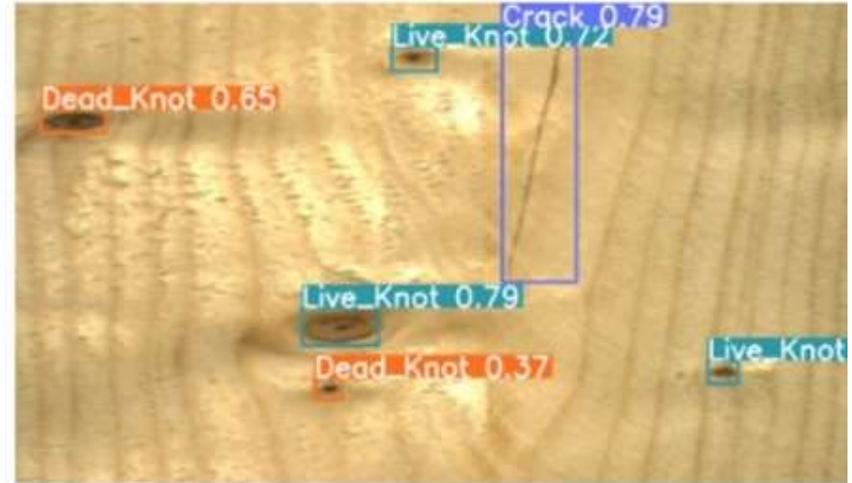Reduced labor costs

Predictive maintenance

Industrial vision & automatic defect detection by AI

Input Image

Classification and localization

Challenges

- Textural complexity of defects and diverse morphological features.

- Variability of the context, resulting from changes in lighting conditions, viewpoints, and occlusions.

- Training deep learning models requires large annotated datasets, but scarce defects—appearing infrequently or unpredictably—make it more challenging.

- Manual annotation is expensive and time-consuming.

- Requirements for real-time inference.

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Few-Shot Learning (FSL)

- Learn from very few examples (typically 1-10 per class).

- Mimics human ability to generalize from limited examples.

- Reduces annotation effort and deployment time.

- Enables rapid adaptation to new defect types.

Paper contributions

- Introduced SSL-YOLO, a method combining contrastive self-supervised learning with the YOLOv8 detector.

- Categorized FSL approaches by their pre-training data source and fine-tuning scope.

- Validated our approach by benchmarking its performance on steel surface defect detection across the defined FSL scenarios.
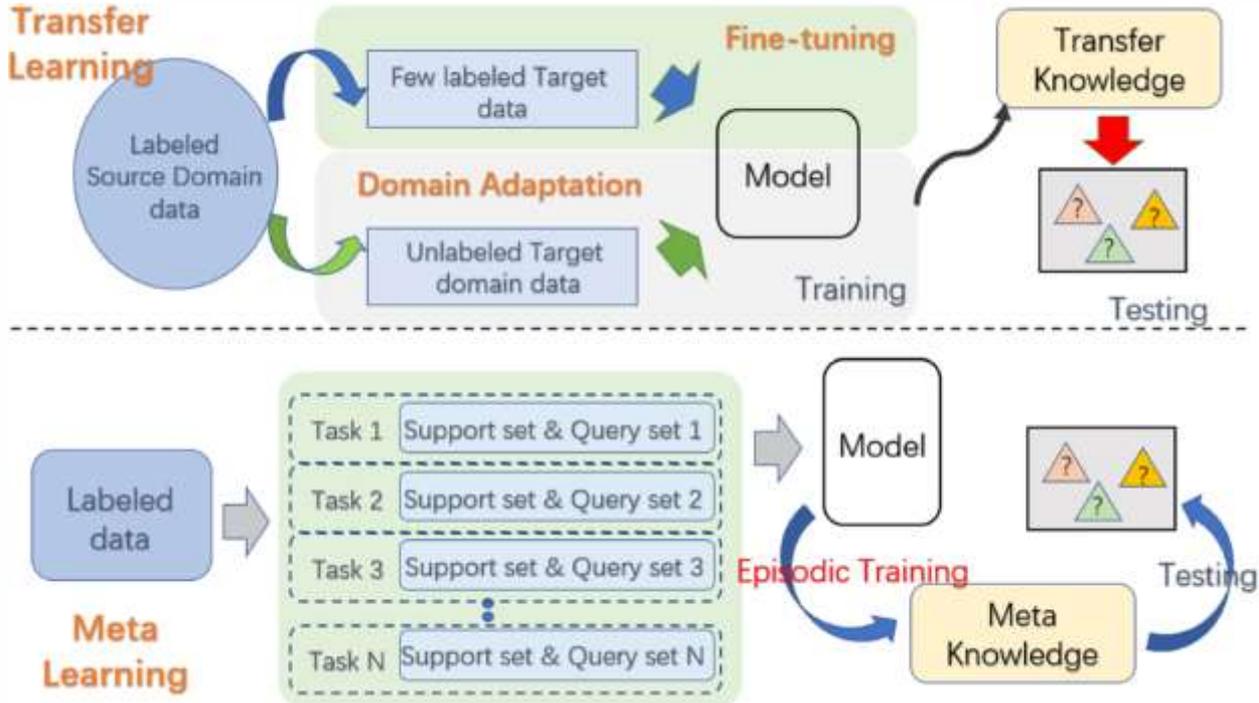
Background

Few-Shot Learning methods :

Transfer Learning vs Meta-Learning
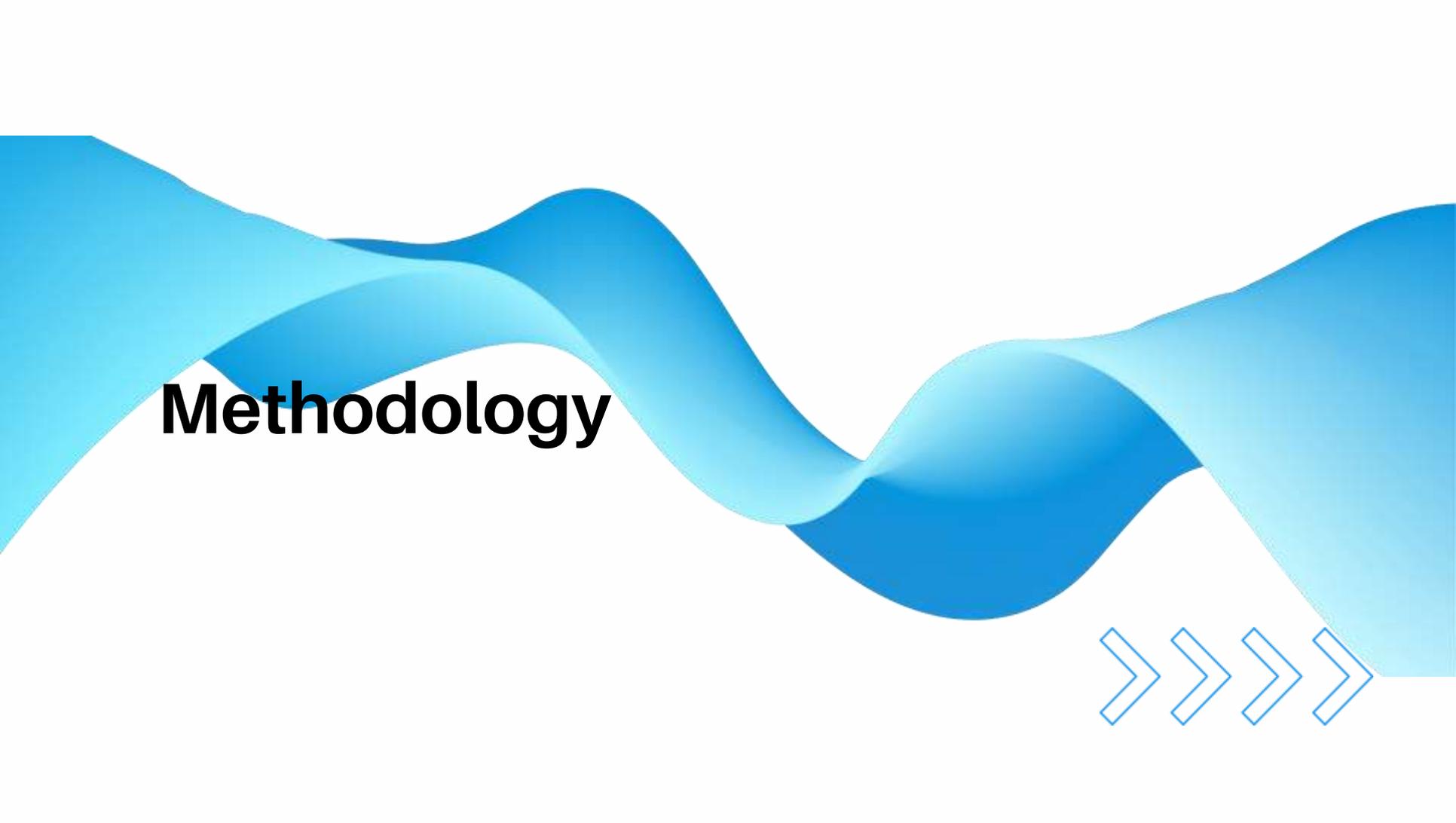
Methodology

SSL-YOLO Overview :
Pipeline

SSL-YOLO Overview :
Contrastive pre-training
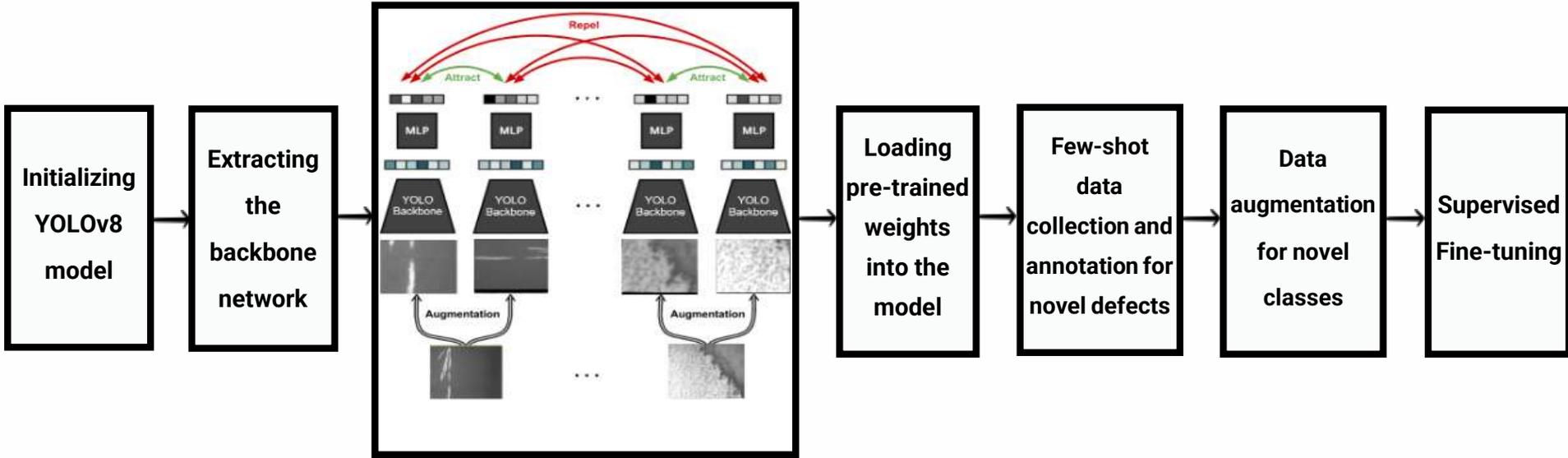
SSL-YOLO Overview :
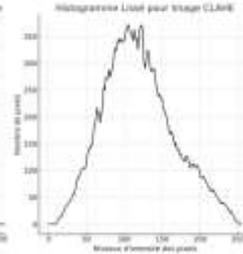## Applied augmentations

Original Image

Brightness and Contrast ColorJitter

Random Translation

CLAHE (Contrast Limited Adaptive histogram equalization)
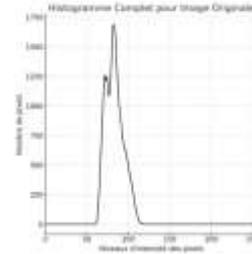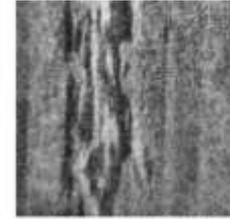
Gaussian Blur

Random Rotation

Random Resized Crop

Dataset for steel surface defects (NEU-DET)

- NEU-DET - Northeastern University Surface Defect Database

- 1,800 grayscale images (200×200 pixels)

- 6 defect categories, 300 images each

- Standard split: 240 training, 60 testing per class

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Dataset for steel surface defects (NEU-DET)
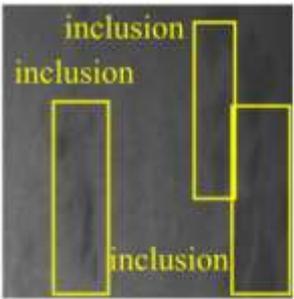
Inclusions
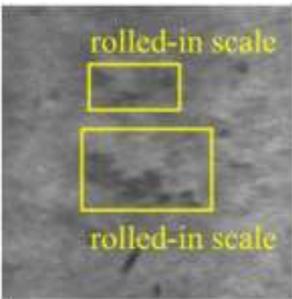
Rolled in scale

Scratches
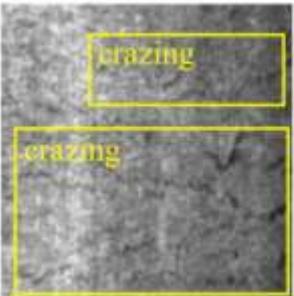
Crazing

Patches

Pitted surface

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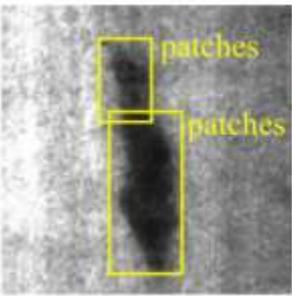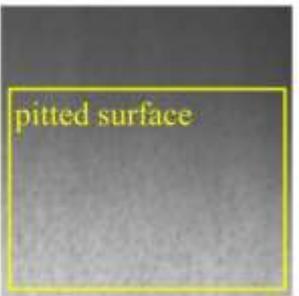
Experimental setup :
Evaluation split

For robust and reproduceable results, we follow the public **F**ew-**S**hot **N**EU-**D**ET (FS-ND) [2] evaluation protocol, performing 10-shot evaluation with 10 labeled examples per class. Results are repeated and averaged across the predefined 100 splits of the novel classes.

Class distributions :
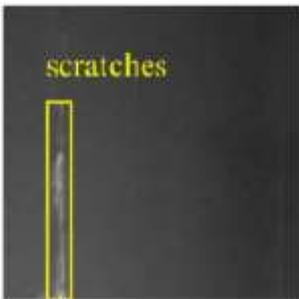- **Base Classes:** Rolled-in_scale, Scratches, Inclusion. (Pre-training phase)
- **Novel Classes:** Pitted Surface, Crazing, Patches. (Few shot fine-tuning phase)
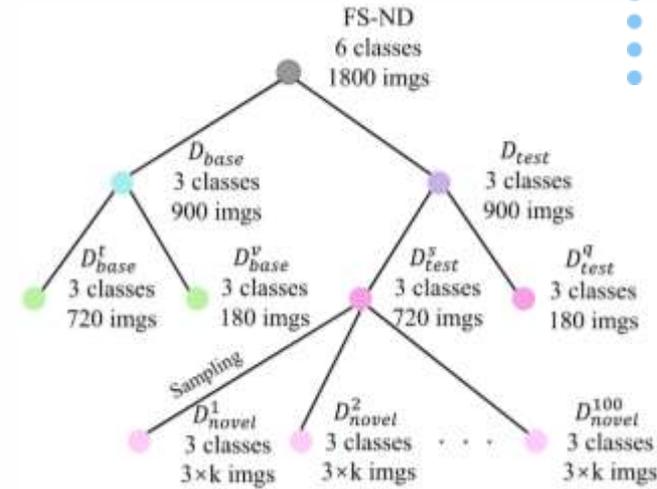
Fig. 5. Structure of k-shot FS-ND, where D^t_{base} is adopted to pre-train models in the base training stage, and D^v_{base} can be utilized to evaluate the performance of pre-trained models. Besides, $D^1_{novel} \sim D^{100}_{novel}$ are 100 groups of support examples for fine-tuning pre-trained models during the few-shot fine-tuning stage, and D^q_{test} serves as a benchmark to contrast the detection accuracy of fine-tuned models. **[2]**

[2] H. Wang, Z. Li, and H. Wang, "Few-Shot Steel Surface Defect Detection," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–12, 2022

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Experimental setup :
Evaluation metrics

○ **Mean Average Precision (mAP@0.5) :**

- Area under Precision-Recall curve

- IoU threshold of 0.5 for detection

- Averaged across all defect classes

○ **Frames Per Second (FPS) :**

- Critical for real-time industrial applications

- Hardware: RTX 4090, batch size 32, 320×320input

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Results & Discussion

Few-shot learning benchmarking scenarios

Scenario	Scope	Pre-training Data	Fine-tuning Data
Cross-Domain Transfer (CDT)	Adapt general model	Large general datasets (e.g., COCO)	Few-shot target defects (all classes)
In-Domain Self-Supervised **Full** Fine-tuning (ISS-FFT)	Leverage abundant unlabeled domain data	Unlabeled target domain images	Few-shot labeled defects (all classes)
In-Domain Self-Supervised **Novel** Fine-tuning (ISS-NFT)	Adapt to new classes	Unlabeled base defect images	Few-shot novel classes only
In-Domain Supervised **Novel** Fine-tuning (IS-NFT)	Update model for new classes	Labeled base defect classes	Few-shot novel classes only

SSL-YOLO 10-Shot mAP@50 Results Across Different FSL Strategies

Cross-Domain Transfer (CDT) - Comparison (10-shot, mAP@50)
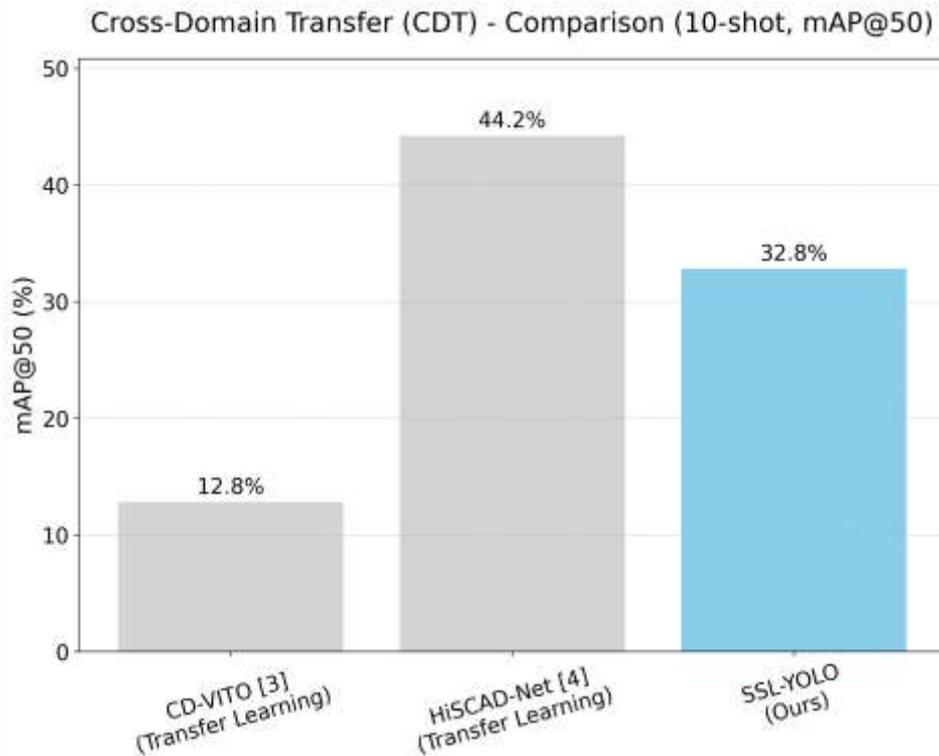
[3] Y. Fu et al., "Cross-Domain Few-Shot Object Detection via Enhanced Open-Set Object Detector," Sept. 27, 2024, arXiv: arXiv:2402.03094.

[4] S. Luo, B. Liu, H. Chen, Z. Wang, R. Yang, and Y. Huang, "Hierarchical Scale Enhancement Network with Contrast Encoding for Few-Shot Liquid Crystal Display Defect Detection," IEEE Sensors J., pp. 1–1, 2025.

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SSL-YOLO 10-Shot mAP@50 Results Across Different FSL Strategies

In-Domain Self-Supervised Full Fine-tuning (ISS-FFT) - Comparison (10-shot, mAP@50)
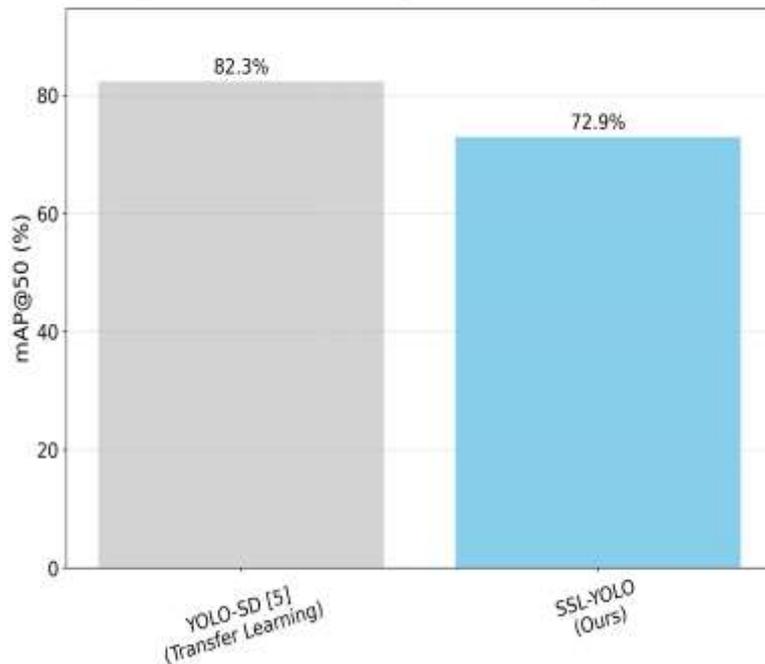
[5] Y. Wen and L. Wang, "Yolo-sd: simulated feature fusion for few-shot industrial defect detection based on YOLOv8 and stable diffusion," Int. J. Mach. Learn. & Cyber., vol. 15, no. 10, pp. 4589–4601, Oct. 2024.

SSL-YOLO 10-Shot mAP@50 Results Across Different FSL Strategies

In-Domain Self-Supervised Novel Fine-tuning (ISS-NFT) - Comparison (10-shot, mAP@50)
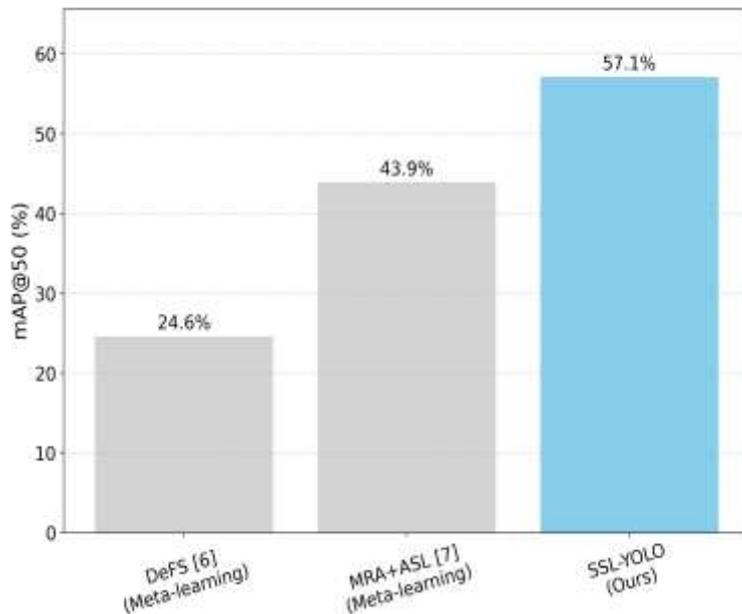
[6] X. Guo, P. Zhang, P. Zheng, Z. Zhang, and J. Liang, "A Decoupled Few-Shot Defect Detection Approach via Vector Quantization Feature Aggregation," IEEE Transactions on Instrumentation and Measurement, pp. 1–1, 2025.

[7] Y. Deng and Y. Song, "Few-Shot Steel Plate Surface Defect Detection with Multi-Relation Aggregation and Adaptive Support Learning," ISIJ Int., vol. 63, no. 10, pp. 1727–1737, Oct. 2023.

# SSL-YOLO 10-Shot mAP@50 Results Across Different FSL Strategies

In-Domain Supervised Novel Fine-tuning (IS-NFT) - Comparison (10-shot, mAP@50)
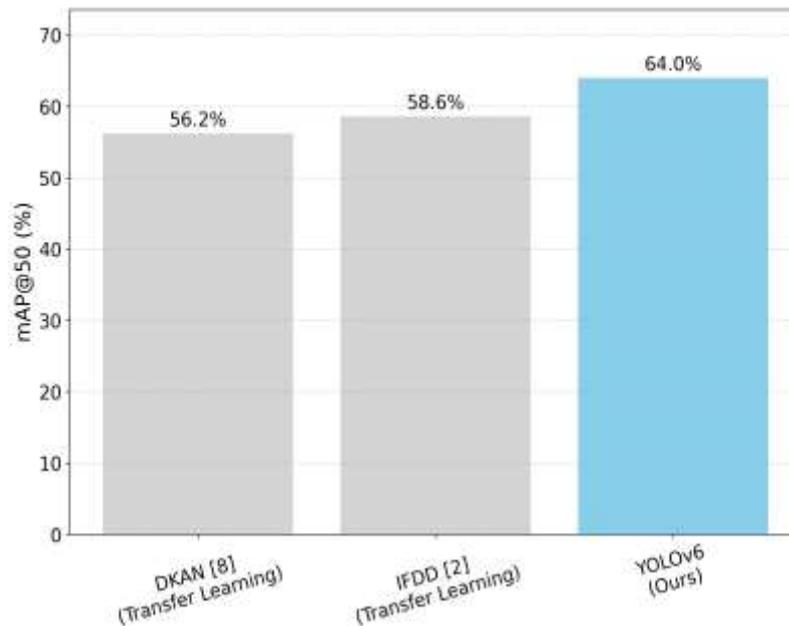
[2] H. Wang, Z. Li, and H. Wang, "Few-Shot Steel Surface Defect Detection," IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1–12, 2022.

[8] C. Sun, L. Gao, X. Li, and Y. Gao, "A New Knowledge Distillation Network for Incremental Few-Shot Surface Defect Detection," 2022.
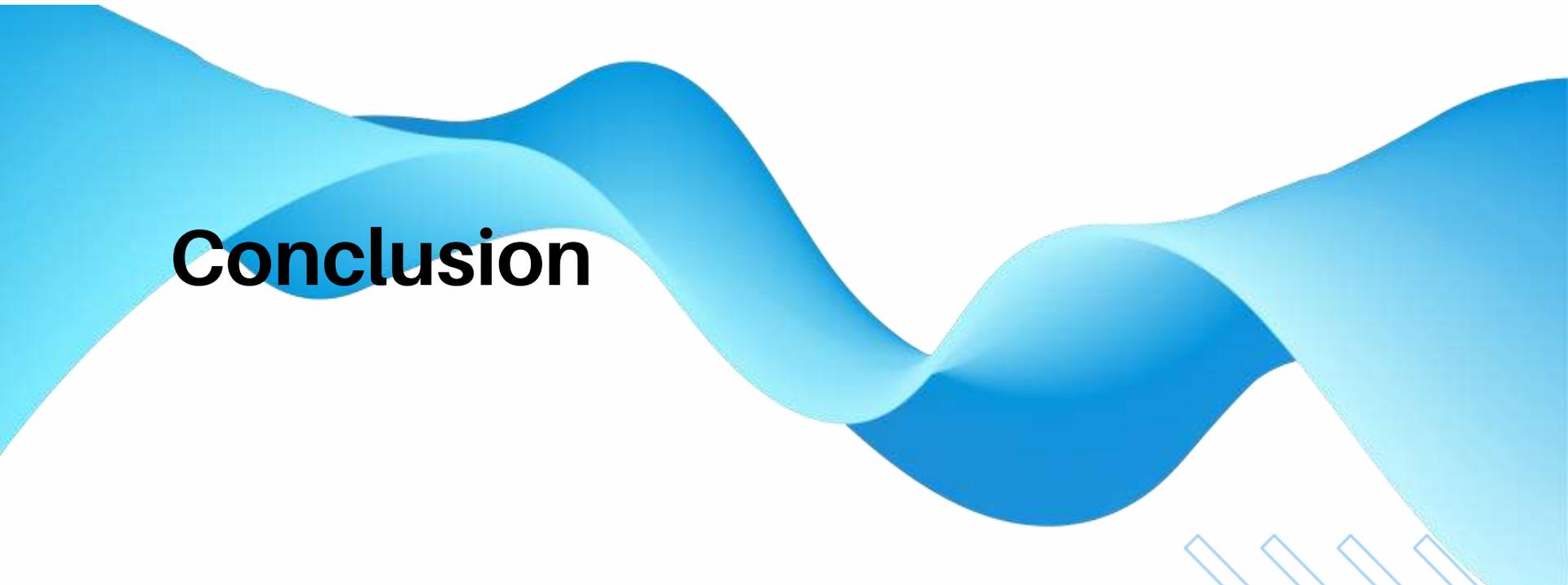
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Conclusion

Conclusion

In-domain pre-training consistently outperforms cross-domain transfer for steel defect detection tasks.

SSL-YOLO effectively leverages unlabeled domain data through contrastive learning, providing a robust initialization for defect detection.

The use of a modern YOLO-family architecture provides a significant practical advantage with inference speeds reaching over 436 FPS.

Ultimately, this provides a practical and performant solution that serves as an accessible alternative to more intricate FSL methodologies, as it requires no specialized modules.

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Thanks for your attention