Journal of Research in Multidisciplinary Methods and Applications
http://www.satursonpublishing.com/
ISSN 2957-3920 (Online) ISSN 3007-7060 (Print)
Volume 4, Issue 8, August 2025

A Screw Surface Defect Detection Model Based on YOLO11- DySample

Zhu Zhenglong[1,*], Liu Wen[2], Ye Zhenhuan[1], Zhang Qiang[1], Zhang Nanqing[1]

1 College of Engineering, Zunyi Normal University, Zunyi, China. 563006; 2 School of Mechanical and Electrical Engineering ,Guizhou Normal University, Guiyang, China, 550025

*Corresponding to: Zhu Zhenglong

Abstract: As critical components in fastening systems, screws play an essential role in structural connection and load transmission, where surface quality directly affects product safety and reliability. To achieve efficient and accurate detection of various surface defects on screws, this paper proposes a detection model based on the YOLO11-DySample algorithm. The proposed method adopts YOLO11 as the backbone detection framework and integrates the lightweight and efficient DySample dynamic upsampling module, which enhances feature reconstruction and improves the perception of small defects. Experimental results on a screw defect dataset demonstrate that the proposed model outperforms other benchmark algorithms in several key performance metrics, achieving a mAP50 of 0.991, mAP50-95 of 0.859, precision of 0.996, and recall of 0.994, indicating excellent accuracy and robustness. Further analysis of loss curves and precision-recall curves confirms the model's convergence and generalization capability. Visual inspection results show that the model can effectively identify typical defects such as scratches and dents, demonstrating strong potential for practical industrial deployment.

Keywords: Screw, Defect Detection, Deep Learning, Image Recognition

1 INTRODUCTION

Fasteners, as essential components in mechanical structures for connection and load transfer, play a critical role in ensuring structural integrity and service reliability [1–3]. The surface quality of fasteners—particularly screws—has a direct impact on product safety and performance. In actual manufacturing processes, various types of surface defects may occur on screws, including scratches, coating irregularities, dents, unprocessed areas, and abnormal surface coloration [4]. These defects can significantly degrade the performance of fasteners and, in severe cases, lead to product rejection and scrapping. Although multiple inspection methods exist, most fastener manufacturing enterprises still rely heavily on manual inspection. This approach is not only inefficient and labor-intensive but also prone to oversight due to operator fatigue and subjectivity, potentially resulting in batch-level product recalls and substantial economic losses.

Conventional methods for industrial surface defect detection primarily include visual inspection, magnetic particle testing, eddy current testing, and machine vision-based techniques [5]. While manual inspection remains widely used, it suffers from low efficiency, high error rates, and heavy dependence on operator experience, making it unsuitable for continuous high-throughput production lines. Magnetic particle and eddy current testing exhibit certain advantages under specific conditions but are limited by strict requirements on surface condition, material type, and electromagnetic properties of the workpiece [6,7], and are easily affected by environmental factors. Moreover, these traditional techniques often fail to provide real-time and comprehensive information about defect morphology and spatial distribution.

In recent years, with advances in computer vision and deep learning, machine vision-based defect detection has become a prominent research focus. This approach integrates image acquisition, preprocessing, feature extraction, and pattern recognition to enable fast and accurate identification of surface defects [8,9]. It offers advantages such as non-contact operation, high precision, and full automation, making it particularly suitable for large-scale industrial applications. Previous studies have demonstrated that deep learning-based frameworks such as YOLO [10], Faster R-CNN [11], and ResNet [12] have achieved promising results in detecting surface defects on industrial components like rail steel [13], magnetic disks [14], and aluminum alloy wheels [15].

However, research on defect detection for small-sized fasteners such as screws remains relatively limited. There is still a lack of dedicated vision-based detection systems capable of handling the complex geometries and subtle defect features typical of such components. To address this gap, this study proposes an automatic detection system tailored for screw surface defect identification in mass production settings. The system integrates

Journal of http://www.satursonpublishing.com/
Research in Multidisciplinary Methods and Applications
ISSN 2957-3920 (Online) ISSN 3007-7060 (Print)
Volume 4, Issue 8, August 2025

high-resolution image acquisition hardware, image preprocessing algorithms, and a lightweight deep learning-based classification network. It is capable of efficiently detecting and accurately classifying multiple types of surface defects on screws, providing a technical foundation for intelligent quality control in fastener manufacturing enterprises.

2 METHODOLOGY

As a widely adopted object detection approach, the DySample-based YOLO11 model proposed in this study enables efficient acquisition and identification of screw surface defects from images.

To improve both the detection accuracy and inference efficiency for screw surface defects, this paper introduces a lightweight and high-performance dynamic upsampling module, DySample, into the single-stage detector YOLO11 [16]. The resulting enhanced model, referred to as YOLO11-DySample [17], is illustrated in Figure 1. The proposed architecture retains the fundamental structure of YOLO11, including its backbone network and multi-scale detection heads. However, traditional upsampling operators in the feature fusion pathway are replaced by DySample modules. This modification facilitates more effective transmission of high-level semantic information to lower-level spatial features, thereby enhancing sensitivity of the model to fine-grained defect regions.

DySample is a parameter-efficient dynamic resampling module that does not require any custom CUDA operations. It maintains a low computational footprint—characterized by reduced parameter count, FLOPs, and inference latency—while offering strong generalization performance. Prior research has shown that DySample outperforms traditional upsampling techniques across various dense prediction tasks, including semantic segmentation, object detection, and instance segmentation [18]. The module dynamically generates sampling offsets and fusion weights based on the input feature map, enabling pixel-level information enhancement. This is particularly advantageous for detecting subtle surface defects on screws, such as scratches and micro-cracks.

As illustrated in Figure 1, the YOLO11-DySample architecture integrates DySample modules into its multi-scale detection branches in place of conventional upsampling layers. These modules work in conjunction with feature fusion blocks such as C2 and C3 to improve overall detection precision of the network without compromising real-time performance. The redesigned architecture preserves the end-to-end efficiency of the original YOLO11 while enhancing robustness and adaptability under complex defect scenarios.

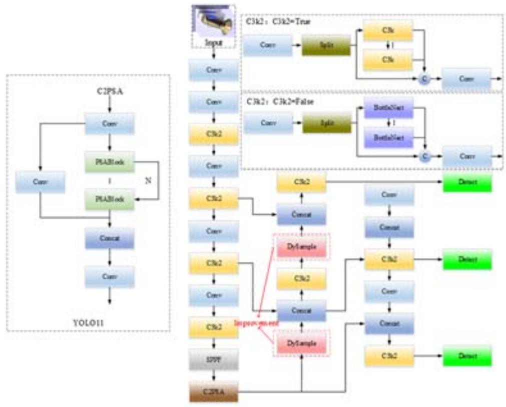

FIGURE 1 YOLO11-DYSAMPLE MODEL STRUCTURE

3 EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the screw surface defect detection experiments, including dataset construction, evaluation metrics, and the comparative results between the proposed YOLO11-DySample model and other methods.

3.1 EXPERIMENTAL DATASET

The dataset used in this study was built using a screw image acquisition system independently developed by the research team in collaboration with an industrial partner. The system consists of a Hikvision MV-CS050-10GC color camera paired with an MVL-KF1228M-12MPE lens. All images were captured at a resolution of 672 × 384 pixels. A total of 4,100 valid screw images were collected to form the dataset for training and evaluation.

3.2 EVALUATION METRICS

To comprehensively evaluate model performance after training, four key indicators were employed:

(1) Precision (P): the proportion of correctly predicted positive samples among all predicted positive samples.

(2) mAP50: mean average precision when the Intersection over Union (IoU) threshold is set to 0.5.

(3) mAP50-95: mean average precision averaged over IoU thresholds from 0.5 to 0.95 with a step of 0.05.

(4) Recall (R): the proportion of correctly predicted positive samples among all actual positive samples.

3.3 EXPERIMENTAL RESULTS

To validate the proposed method, three comparison models were selected: YOLO11-UpSample-Conv, YOLO11-C3K2Ghost-all, and YOLO11-DWConv. All models were evaluated using the aforementioned metrics, and the results are summarized in Table 1.

Journal of http://www.satursonpublishing.com/
Research in Multidisciplinary Methods and Applications
ISSN 2957-3920 (Online) ISSN 3007-7060 (Print)
Volume 4, Issue 8, August 2025

TABLE 1 COMPARISON RESULTS OF DIFFERENT METHODS

Method	P	mAP50	mAP50-95	R
YOLO11-UpSample-Conv	0.975	0.994	0.76	0.987
YOLO11-C3K2Ghost-all	0.996	0.994	0.746	0.974
YOLO11-DWConv	0.992	0.994	0.75	0.981
YOLO11-DySample	0.996	0.995	0.859	0.994

Among the four improved YOLO11-based models, a comprehensive analysis based on precision, recall, mAP50, and mAP50-95 yields the following observations:

First, as shown in Table 1, the YOLO11-DySample model achieves the highest precision (0.996), recall (0.994), and mAP50-95 (0.859) on the validation set, indicating superior capability in detecting multiple types of screw defects with high stability. As illustrated in Figure 2, the P-R curve of this model maintains excellent precision even in high-recall regions, suggesting a favorable balance between precision and recall with minimal false positives. By contrast, YOLO11-C3K2Ghost-all also reaches a high precision of 0.996, it exhibits relatively lower recall (0.974) and mAP50-95 (0.746). The slight decline observed in its P-R curve at high recall levels indicates limited ability to detect fine-grained or ambiguous defects, resulting in a higher risk of missed detections. The YOLO11-C3K2Ghost-all model demonstrates strong false-positive suppression capability, as reflected by its high precision, but its overall performance in recognizing subtle or edge-blurred defects remains suboptimal. Meanwhile, the baseline model YOLO11-UpSample-Conv shows balanced performance across all metrics (P = 0.975, R = 0.987, mAP50-95 = 0.760), serving as a reliable reference. Nevertheless, its accuracy and efficiency remain inferior to those of the proposed YOLO11-DySample framework

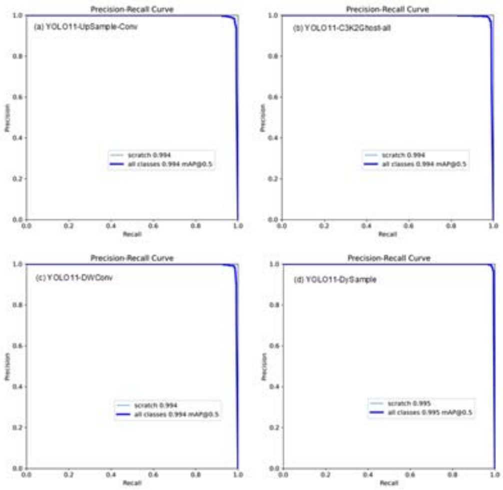

FIGURE 2 P-R CURVES OF MAP50 WITH DIFFERENT ALGORITHMS

To further verify the training stability and generalization capability of the optimal YOLO11-DySample model, both training and validation loss curves were plotted. As seen in Figure 3, the training loss consistently decreases and stabilizes over time, while the validation loss exhibits smooth convergence without significant oscillation or overfitting. This confirms that the model maintains strong generalization during training.

The small gap between training and validation losses in later epochs further indicates that the designed network architecture and parameter settings effectively fit the training data while preserving robust performance on unseen samples. This is consistent with the high precision and recall observed in the P-R curve, validating the reliability of YOLO11-DySample in screw surface defect detection tasks.

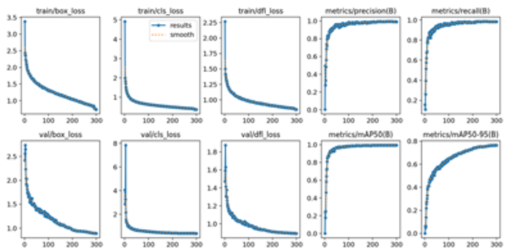

FIGURE 3 LOSS CURVES OF MODEL TRAINING AND VALIDATION

Finally, to visually demonstrate the practical performance of the proposed model, representative detection results on screw images are provided in Figure 4. The YOLO11-DySample model accurately detects a variety of defects—including surface scratches, dents, and color anomalies—with precise boundary localization and correct defect classification, showcasing strong detection robustness.

Journal of Research in Multidisciplinary Methods and Applications
http://www.satursonpublishing.com/
ISSN 2957-3920 (Online) ISSN 3007-7060 (Print)
Volume 4, Issue 8, August 2025

Even under complex backgrounds or multi-target interference conditions, the model retains high stability without significant false positives or missed detections. These results further confirm comprehensive performance advantages of the model, particularly in capturing small-scale and fine-grained defect features. Pixel-wise feature enhancement achieved by the DySample module plays a crucial role in this improvement, leading to detection outputs with precise alignment to actual defect distributions.

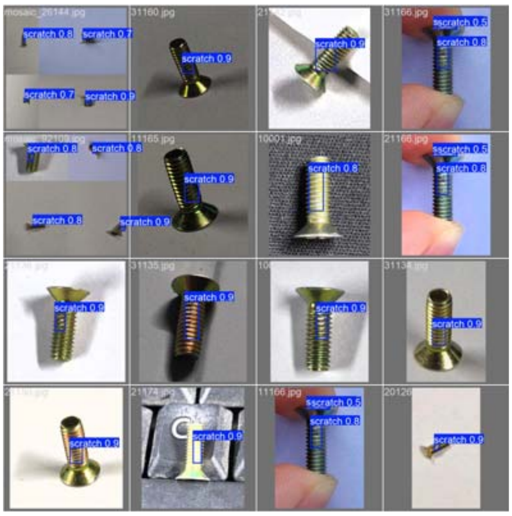

FIGURE 4 DETECTION EFFECT

In summary, the YOLO11-DySample model demonstrates superior performance in both detection accuracy and stability, offering an effective solution for screw defect detection.

4 CONCLUSION

To address the inefficiencies and high miss rates associated with manual surface defect inspection in fastener production, this paper proposes an automatic screw surface defect detection method based on an improved YOLO11 backbone network. By integrating the DySample upsampling module, the model significantly enhances feature restoration and spatial alignment capabilities, thereby improving its sensitivity to small targets and defects with ambiguous boundaries. Comparative experiments among multiple improved models demonstrate that the proposed YOLO11-DySample model achieves the best performance across key metrics, including precision, recall, and mAP50-95. These results confirm superior detection accuracy and robustness of the model, making it a promising solution for intelligent quality inspection in fastener manufacturing.

FUNDING

Funding Contract No.: Zunshi Kehe HZ Word[2023] No.152；Qiankehe Zhongyin Di [2024] No. 018；Zunshi Kehe HZ Zi (2023) No. 163；Zunshi XM [2023] No. 1-02;Zunshi Kehe HZ Zi (2023) No. 161; Zunshi CXY [2024] No. 08.

REFERENCES

[1] Li Ya, Liu Ruicheng, Ding Yanyu, Hao Xiaoqi. Research on Bolt Geometric Defect Detection and Measurement System[J]. Machinery Design & Manufacture, 2025, (03):366-371.

[2] Yang Fei, Luo Jianqiao, Li Bailin, Xiong Ying. Rivet Surface Defect Detection Based on NRLBP Combined with Noise Estimation[J]. Machinery Design & Manufacture, 2021, (04):56-61.

[3] Zhao Na. Research on Semantic Segmentation Network Based on U-Net++ Rivet Surface Defect Detection[D]. Donghua University, 2022.

[4] Zhang Yingning. Research on Defect Detection of High-speed Train Floor Bolt Based on Deep Learning[D]. Nanjing University of Posts and Telecommunications, 2020.

[5] Li Shaobo, Yang Jing, Wang Zheng, Zhu Shude, Yang Guanci. Review of Development and Application of Defect Detection Technology[J]. Acta Automatica Sinica, 2020, 46(11):2319-2336.

[6] Liu Wei, Li Rubin, Cao Meng, Li Rong, Wang Xingqiang. Application Study on Nondestructive Testing Technology in the C6 Repair of Harmonious Locomotive Traction Motor [J]. Railway Locomotive & Car, 2018,38(02):100-102+106

[7] Li Wenjun. Common Problems in Eddy Current Testing of Nonferromagnetic Heat Exchanger Bundle[J]. China Petroleum and Chemical Standard and Quality, 2018, 38(14):47-48.

[8] Ma S, Wu N, Li X. Deep learning with big data: State of the art and development[J]. CAAI Trans Intell Syst, 2016, 11, 728-742

[9] Zhang Z, Pang W, Xie W, Lv M, Wang Y. Deep Learning for Real-time Applications: A Survey[J]. Softw, 2020, 31, 2654-2677.

[10] Li Jun, Xu Xuanhao, Wang Yaohong. Rail surface defect detection algorithm based on improved YOLOv5s[J]. Journal of Chongqing University of Technology(Natural Science), 2024, 38(08):130-137.

[11] Pan Tian, Hui Kaifa. Aircraft Skin Defect Detection Method Based on Improved Faster R-CNN[J]. Mechanical Engineering & Automation, 2025, 54(02):139-141.

[12] Ding Guanhua, Yao Xu. Metal Surface Defect Detection Model Based on Improved Resnet50[J]. Computer Measurement & Control, 2025, 33(05):62-68+78.

[13] Geng Na. Research and Application of Rail Surface Defect Detection Based on Improved YOLOv7-tiny[D]. Dalian Jiaotong University,2025.

[14] Ding Yong, Hong Tao. Defect Detection of Magnetic Disk Based on Improved U-Net Convolutional Neural Network[J]. China Standardization, 2021, (13):192-198.

[15] Yan Xueshun, Wang Donghong, Wu Wenyun, Jiang Miao, Qiu Huihui, Gong Qianhai, Shu Da. Image Defect Detection of Aluminum Alloy Wheel Hub Casting Based on Deep Learning[J]. Special Casting & Nonferrous Alloys, 2023, 43(04):457-463.

[16] Khanam R, Hussain M. YOLOv11: an overview of the key architectural enhancements[J]. arXiv:2410. 17725, 2024.

[17] Wenze Liu, Hao Lu, Hongtao Fu, Zhiguo Cao. YOLOv11: an overview of the key architectural enhancements[J]. arXiv:2308. 15085, 2023.

[18] Ruxiao Yang, Yanru Lee, Fushin Lee, Zhenying Liang, Nanhua Chen, Yang Liu. Improvement of YOLO Detection Strategy for Detailed Defects in Bamboo Strips. Forests 2025, 16, 595.