

Comparative Analysis of Yolo Variants for Rail Surface Defect Detection Using an Enhanced Yolov5

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ABSTRACT: This study deals with the comparison of different versions of YOLO and then addressing the problem of detecting surface defects in load-carrying rails within automobile assembly environments, which are industrial environments requiring very high precision and reliability. In order to address the challenges posed by the complexity and variability of such defects, we introduce a novel detection system based on an enhanced YOLOv5 architecture specifically developed to meet the rail surface inspection needs. The detection system utilizes advanced computer vision strategies in conjunction with deep learning enhancements to provide accurate and robust detection of defects. The Multi-Scale Pyramid Pooling (MSPP) module is a significant part of the system that extracts rich features at multi-scales, using residual stacking. Additionally, we introduced a new Dual Attention Mechanism (DAM) to re-focus the model's attention on small and irregularly shaped surface defects. This has been one of the challenges with traditional models.

Experimental results validate the adequacy of the framework, as evidenced by the adjacent model's AP50 of 97.3%, representing a 4.2% improvement over the former YOLOv5. The adjacent model has a mean Average Precision (MAP) of 88.9%, with a corresponding recall of 91.4%, and an accuracy of 92.6%, all demonstrating competent performance across important parameters. The results emphasize the possibility of the framework's practical use in automatic rail defect detection; as a reliable solution for quality assurance in an industrial domain, the framework is shown to be highly accurate.

Keywords: YOLOv5 architecture, Multi-Scale Pyramid Pooling, Dual Attention Mechanism, surface defects.

1. Introduction

Load-carrying rails are a critical element within automobile production factories to achieve stability and smooth running. But excessive use and harsh conditions will deteriorate and cause structural collapse after a while. If not addressed, they are severe safety hazards, cause expensive maintenance, and in worst-case scenarios cause catastrophic failure. One of the most common examples of such a failure is the 2018 Chongqing Changan Automobile workshop accident, which

underlined the need to install effective defect detection systems in order to avoid workplace accidents. To solve this problem, we developed an intelligent fault detection system for load-bearing rails. This solution employs an improved YOLOv5 model with advanced machine vision and deep learning functionality to accurately detect surface defects [11], [12], [13], [14],[15]. In addition, with the incorporation of real-time adaptability, co-learning, and data upgrade algorithms, our system enhances accuracy and reliability, thus presenting an extremely valuable

Autonomous vehicles can learn to detect pedestrians, cars, and street signs to make driving safer. Security and surveillance applications are detecting unwanted behaviors as they happen. Medical imaging assists a physician in diagnosing illness through detection of problems in medical images. Industrial automation is monitoring

machines and ensuring safety in manufacturing environments.

Along with continued improvements in deep learning, new editions of YOLO continue to increase both speed and precision, strengthening its position as a leading method for realizing real-time object identification in many sectors[2]

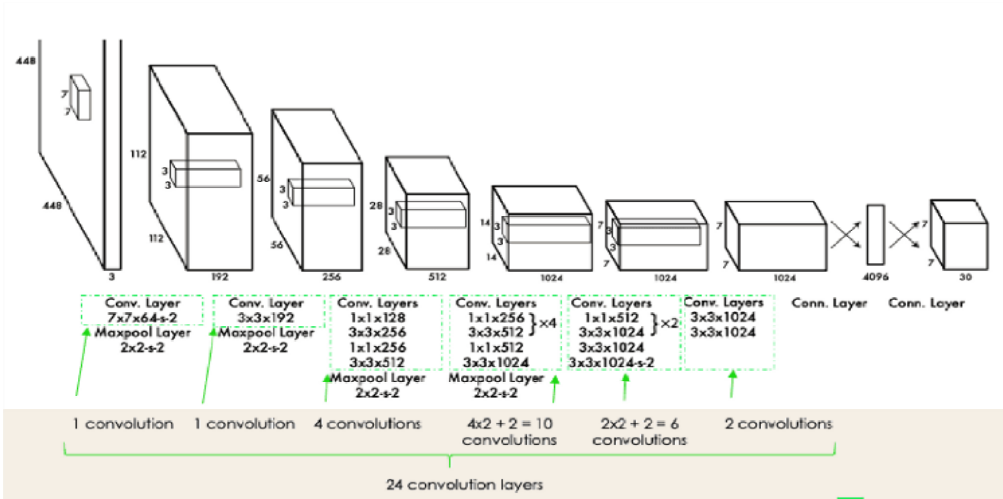


Figure 2 : YOLO Architecture

3. YOLO Versions

Table 1: Summary of Improvements on YOLO

S/N	YOLO Variant	Improvement	Results
1.	YOLOv1 (Redmon et al., 2016)	Single shot detector combines and solves the problem of drawing boundary boxes and class identification	Higher accuracy and speed compared to twostage object detector such as Faster R-CNN
2.	YOLOv2 (Redmon & Farhadi, 2018)	Iterative improvements on Batch Normalization, higher resolution detection and use of anchor boxes	Reduction in architecture, faster detection and higher accuracy and better detection of high resolution images
3.	YOLOv3 (Redmon & Farhadi, 2018)	Addition of objectness score to bounding box prediction, added connections to the backbone network layers and predictions at three separate granularities.	Improves detection of smaller objects
4.	YOLOv4 (Alexey et al., 2020)	Improved feature aggregations, bag of freebies with mosaic augmentations and use of mish activation	Achieved improved accuracy and ease of training, high quality performance and accessibility
5.	YOLOv5 (Nepal & Eslamiat, 2022)	Reduced network parameters, use of Cross Stage Partial Network (CSPNet) for the head, PANet for the neck of the architecture, residual structure and auto-anchor. It also utilizes mosaic augmentations.	Extremely easy to train, inference on individual, batch images, video feed and webcam ports. Ease of transfer and use of weights. Faster and more lightweight than previous YOLO.
6.	YOLOv6 (Chuyi et al., 2022)	Redesigned network backbone and neck to EfficientRep Backbone and Rep-PAN Neck. The Network head is decoupled separating different features from the final head	Improvement in detecting small objects, anchor free training of model. Less stable and flexible as compared to YOLOv5.
7.	YOLOv7 (Wang et al., 2022)	Layer aggregation using E-ELAN, trainable bag of freebies, 35% fewer network parameters. Model scaling for concatenation-based model	Increase in speed and accuracy, ease of training and inference.

3.1 YOLOv4

YOLOv4 is made up of three main parts:

(a) Backbone - CSPDarknet53: The backbone network identifies the specific and unique higher-level features of the image data and combines visual information necessary for detection.

(b) Neck - SPP and PAN: The neck combines scales together in the neck to aggregate features through the Spatial Pyramid Pooling (SPP) method and exchange information between high and low levels of the Path Aggregation Network (PAN). The neck should enhance the model's ability to detect objects of scale and shape.

(c) Head - YOLOv3 Detection Head: This is where the final predictions occur. In the detection head bounding boxes are made as well as probabilities of classed predictions for the model to both detect and place the objects in the image.

YOLOv4 integrates a multitude of state-of-the-art algorithms [32] that enhance detection performance without compromising speed. The improvements can be separated into two baskets: Bag of Freebies (BoF), which improve training time and effort without slowing down inference, and Bag of Specials (BoS), which improve accuracy without much (or any) cost to inference

time. BoF and BoS improvements are applied both in the backbone and detector portions of the network. Background improvements (BoF) utilize data augmentation in the form of the Mosaic and CutMix approach to increase diversity of the dataset, DropBlock for regularization, and label smoothing to provide less confidence around the classification. Performance improvements (BoS) utilize the Mish activation function for smoother training, connections labeled CSP (which stands for "Cross Stage Partial") to eliminate redundancy, and MiWRC to better allow the flow of features across layers.

The BoF (Training Enhancers) employs CIoU loss for improved bounding box accuracy, CmBN for better cross-batch consistency, and Self-Adversarial Training for enhanced model robustness [34]. Additional aspects include many anchors per object, variable image sizes during training, less grid sensitivity, and cosine annealing for the learning rate schedule. BoS (Performance Boosters): This improves detection through SPP for multi-scale features, SAM for attention refinement, PAN for feature fusion, and DIOU-NMS for accurate filtering of objects after processing. With all of these improvements, YOLOv4 becomes a very fast, accurate, and incredibly efficient model- perfect for real-time object detection situations.

3.2 YOLO V5

Shortly after YOLOv4 gained popularity in the area of object detection, Glenn Jocher and several of his associates at Ultralytics produced YOLOv5. The biggest part of the novelty was the shift away from the prior Darknet platform towards PyTorch, a newer and friendlier deep learning framework that is sometimes more appealing to developers. This change made it much easier for developers and researchers to build, train, and deploy detection models that can be used in many tasks and applications.

YOLOv5 is much more than just a manufacturer of a framework; it has produced great improvements in speed, accuracy and overall

performance. Here's a brief overview of how it works:

1. Backbone (CSPDarknet53) The backbone is where it all starts. It is responsible for extracting features from the input images. YOLOv5 relies on CSPDarknet53, which is both fast and effective. It improves training and prediction speeds, even more so by dropping unneeded calculations and still achieving strong accuracy—an improvement over the previous YOLO models, YOLOv3 and YOLOv4.

2. Neck: PANet and SPP Following the backbone is the neck, which serves as a connector between the output features and detection layers. YOLOv5 incorporates a Path Aggregation Network (PANet), which allows features to be better shared and communicated between feature levels, especially in situations with small object detection or when objects are partially occluded. Additionally, there is a Spatial Pyramid Pooling (SPP) block, which enables the model to "pool" from different scales to better detect objects that are of different shapes and sizes.

3. Head: Forecasting across Scales The head sits at the end of the pipeline and is a forecasting system. YOLOv5 creates this capability by detecting objects of small, medium, and large sizes in a single inference run, using three separate feature maps. To create more accurate predictions, YOLOv5 deploys a novel loss function called GIoU (Generalized Intersection over Union) which is a more robust measure of alignment between predicted boxes and the actual placement of items[2].

What Makes YOLOv5 Different. High-Speed Detection: The updated backbone allows for faster real-time detection than previous versions. Accurate: YOLOv5 uses PANet and SPP to support small object detection in large scenes. Developer Friendly: YOLOv5, based on PyTorch, is easy for you to train, modify, and deploy in your applications.

In what industries is YOLOv5 utilized? With its accurate and rapid performance, YOLOv5 has a

variety of applications across a diverse selection of industries; including: Self-Driving Vehicles - In order to detect people, vehicles and traffic signals in real-time. Security and Surveillance - For smart surveillance of people and events with precision tracking. Health Care - To help examine medical images for rapid assessment of potential issues. Smart Manufacturing - To monitor machinery and production lines for safety and efficient productivity.

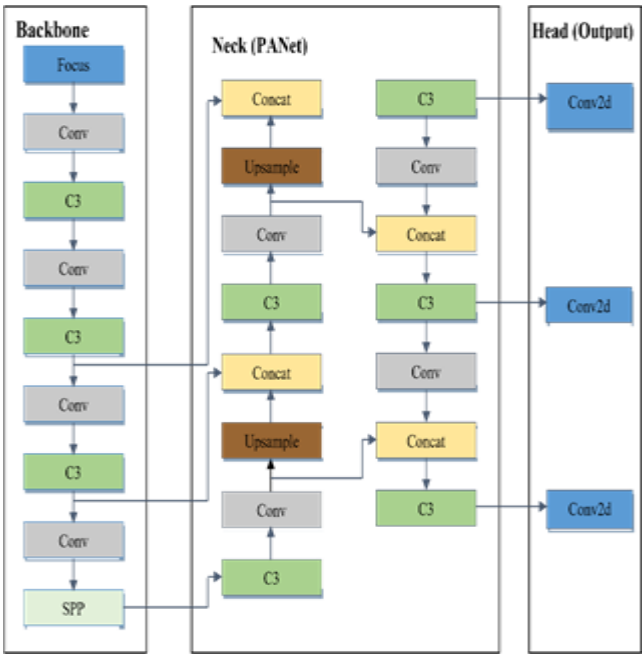


Figure 3 : YOLOv5 Architecture

3.3 YOLOv7

YOLOv7: Advancing Real-Time Object Detection YOLOv7 is the most advanced model in the YOLO (You Only Look Once) family and is already revolutionizing the field of computer vision. The novelty in this case is not in the speed or improvement in accuracy, but in the way it was developed. Rather than rely on pre-trained weights and an additional dataset as is often the case, YOLOv7 was entirely from scratch using only the MS COCO dataset (Wang et al., 2022).

But what is the larger game changer? It does all of this with a very efficient use of resources. YOLOv7 reduces the number of parameters to around 40% and computation by around 50% compared to other cutting-edge models. This translates into faster processing, lower power use,

and greater flexibility—especially on deployment to devices with limited hardware. E-ELAN: Enabling the Network to Learn Smarter, Not Harder. At the core of YOLOv7's stellar performance is a new architectural enhancement called E-ELAN—short for Extended Efficient Layer Aggregation Network. It is designed to allow the model to learn more effectively while also reducing complexity for training [2].

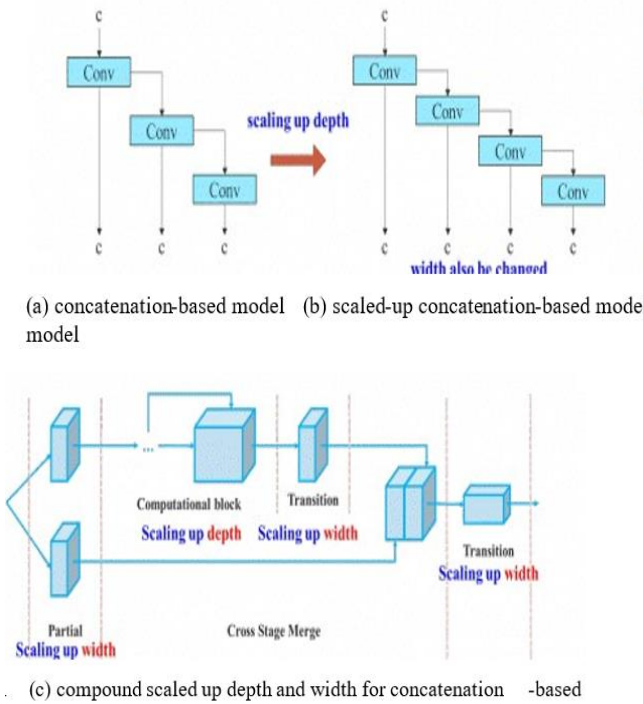


Figure 4: Model Scaling of YOLOv7

Moving from scenario (a) to (b), we see that increasing the depth of concatenation-based models also unintentionally increases output width of the computational blocks, which quickly passes to the next transition layer and potentially disrupts the overall structural equilibrium of the model. To address this issue, scenario (c) incorporates a better scaling option—modifying only the depth of computational blocks, and only modifying width in transition layers. This topological adjustment for scale maintains architectural balance and further helps with scaling the efficacy. While YOLOv6 performs exceptionally well in detection accuracy, it does not scale or offer the same user-friendliness that YOLOv5 and YOLOv7 do. They are significant for this study due to their ability to handle single-image inference, to not lag behind YOLOv5 and

YOLOv7 when multiple images begin detection; particularly, YOLOv6 does not balance accuracy or performance when tackling multiple images (Banerjee, 2022). For all the reasons above, to perform and conduct exploratory analysis this study will utilize YOLOv5 and YOLOv7, as they provided better performance, particularly for multi-object detection, but also a simplified experience for test and training to customize inference.

4. Methodology and Design

This research presents a robust and adaptable framework that determines defects in load bearing rails, a critical component in an automotive assembly line. The framework includes a modified YOLOv5 model [33] that has been carefully fine-tuned to yield reliable defect identification, down to fine surface defects. The structure of the designed EHA-YOLOv5 framework is shown in Figure 2, with accompanying labeling for clarity. This work is unique in that it combines deep learning and advanced machine vision, while also combining a high level of adaptability in various settings in industry; the study explores model tuning to accommodate operational differences in the situations, with domain-based optimization, fine-tuning for the operational situation, and transfer learning. Real-time responsiveness, collaborative learning features, and intelligent data augmentation augment its effectiveness by ensuring consistent results even amidst challenging and fast changing conditions.

This paper introduces multiple structural enhancements to the architecture of YOLOv5 to improve detecting surface defects in load bearing rails [24]. Load bearing rails are important components in automotive manufacturing environments. Initially, a Multi-Scale Pyramid Pooling (MSPP) module is used in place of the typical Spatial Pyramid Pooling module. This improvement includes modeling defects located at multiple scales with varying levels of complexity. To enhance detection performance, the model integrates a Dual Attention Mechanism (DAM), which allows the model to pay attention to the

most distinguishing areas of each image and improves its ability to detect small or invisible surface defects. Lastly, to maintain better representations by retaining more key characteristics as well as greater completeness in representation across the network, a Down-Sampling with Temporal Modeling (DSTM) block is used in place of typical down-sampling blocks.

For optimal flexibility of the model with respect to the actual size distribution of surface anomalies, we used a clustering method called Density-Based Dual Attention Module Network (DBDAMN). This enabled better localization and classification through anchor box dimension optimization. These modules have been combined into one system within the proposed EHA-YOLOv5 network architecture, as depicted in Figure 2. Overall, these advances represent noticeable enhancements to the network's feature extraction capacity and detection accuracy for small surface anomalies on load-bearing rails.

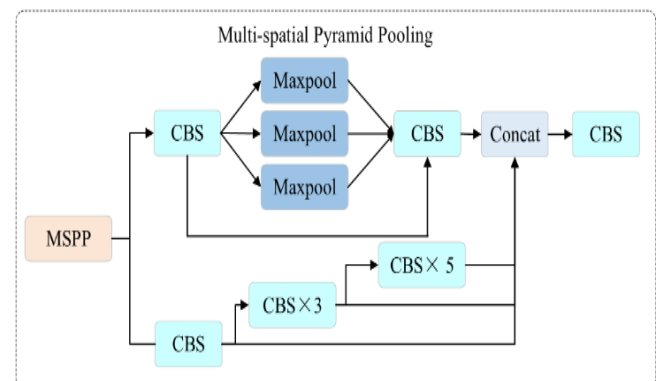


Figure 5: structure of MSPP

Traditional YOLO-based object detection strategies often face difficulties when applied to rail surface inspection applications due to the irregular distribution, geometry, and small sizes of many surface anomalies. In addition to making detection more challenging, factors can make object detection models less reliable for true applications in industry, where the increased risk for false negatives and false positives can result in undesirable outcomes. To mitigate these issues, we proposed the Dual Attention Mechanism (DAM) of the EHA-YOLOv5 framework as part of the major contributions to promote the model's

sensitivity and accuracy for complex, small defect detection in pieces of rail. The DAM module is critical, as it invokes spatial attention in the network around the most discriminative features, particularly features that have small, irregular fault geometries. The DAM raises attention on both the spatial and channel aspect, giving a better model that can segregate damaged areas from typical rail texture. This directed attention improves the probability of detection due to surface defects being more subtle than traditional detection

strategies of other defects potentially would. The addition of DAM also improves the ability of YOLOv5 architecture to fuse features at different scales, which is favorable when reference to the large differences in potential defect shapes and sizes in load-bearing rail systems. Use of scaled resolution information means a greater and more reliable detection framework is assembled for complex inspection conditions in industry while maintaining a fine-grain characteristic either full or in the transfer learning across resolutions.

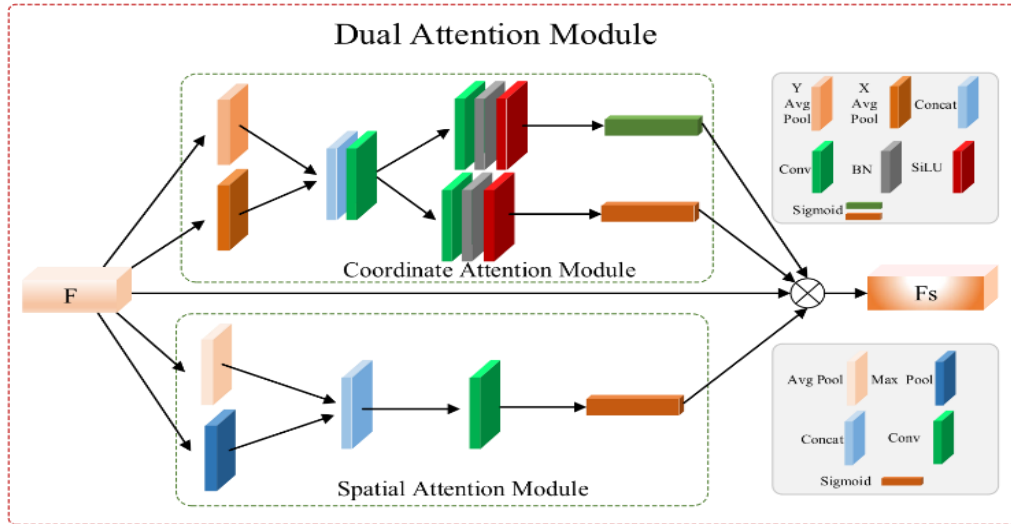


Figure 6: structure of DAM

5. Multi-Model Compare

COMPARISON WITH COMMON MODELS To investigate the potential of our proposed model for detecting surface defects on load-bearing rails, we compared it to some of the most common object detection models such as Faster R-CNN[29], YOLOv4[30], YOLOv5, and YOLOv7[31]. To ensure uniformity and fairness, the detection models were trained on the same dataset. Therefore, Table 5 summarizes the results of our comparison. The following describes the performance of our updated YOLOv5 model: Recall: Our model achieved a recall of 91.4%, which is 6.4% better than YOLOv4, 8.2% better than Faster R-CNN, and 2.2% better than YOLOv7. This indicates the model is better able to identify very small or complex defects, especially in dense or active environments.

Precision: Our model achieved a Precision of 92.6%, demonstrating an improvement over

alternative systems by 1.0% to 1.4%, in terms of decreased false positives and reliable identification of true faults. mAP (mean Average Precision): Similarly, mAP improved from 87.8% to 88.9%, suggesting a consistent rate of detection across varying fault types and sizes. The advancements are mainly attributed to the feature extraction, and multi-scale detection capability of the model to perform reasonably in real-world inspection scenarios. Conclusion: In summary, our modified YOLOv5 model excels in all of the performance measures. Overall, it still has the potential for automation in rail defect detection given it can detect minor, small, and complex surface defects.

6. Multi-Model Visualization Comparison

We performed a visual assessment on three separate fault scenarios in order to show that our construction may work in a real application (Figure 7). Crash Sample: This was a test with one

larger and one smaller fault. Our model, featuring a Dual Attention Mechanism (DAM), was the only model to track the smaller fault. All models were able to track the large fault, but the other models (Faster R-CNN, YOLOv4, YOLOv5, and YOLOv7) did not detect it. Our model had the highest detection accuracy (89%) and anchor placement, while every other model had an accuracy of less than 83%. Damage Sample: This sample had several medium-sized faults. In the case of anchor box placement, the majority of models overshot or undershot the targets. Our model distinguished itself by localizing every single fault and achieving a maximum detection accuracy of 91%.

7. Evaluation and Discussion

This study addresses an important problem in industrial automation: detecting surface defects on load-bearing rails used in automobile assembly

lines. Conventional approaches typically engage in acceptable levels of precision, along with high rates of misses, and high false alarm rates when considering small, hidden or inconspicuous defects.To address these problems we developed an advanced YOLOv5-based detection system that integrates deep learning with machine vision. The solution consists of a number of advanced modules:• Re-clustering anchor boxes, with the DBDAMN algorithm, provides useful computation reduction without harm to the level of accuracy.• The MSPP Module helps to create a better deep representation, helps to eliminate chance of gradient vanishing, and enhances the depth of the backbone network by creating combinations of representations at multi-scale levels.•The DAM Module helps to address the attention to small defects by enhancing the attentional mechanisms among the PANet and the backbon

Table 2: Model comparison [1].

Model	Recall	Precision	mAP
Faster R-cnn	80.8	87.2	83.6
YOLOv4	82.6	86.8	81.3
YOLOv5	89.0	88.2	87.8
YOLOv7	86.8	87.5	86.2
YOLOv5 (ours)	91.4	92.6	88.9

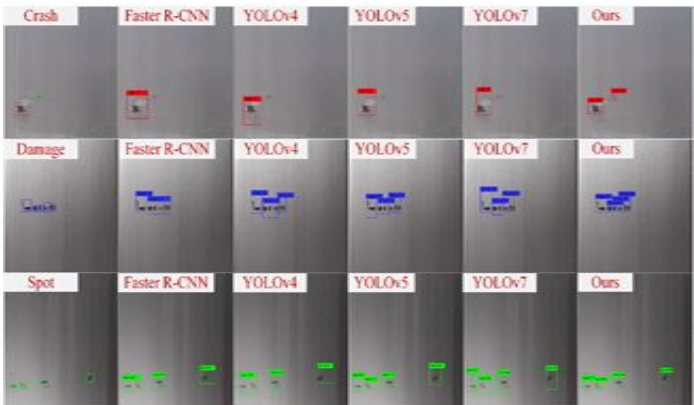


Figure 7: Detection results of different recognition models

8. Conclusion

This research addresses the persistent problem of detecting surface anomalies of load-bearing rails in automotive assembly lines, which has been given increased attention in today's manufacturing ecosystem. Our response is the proposition of a multi-layer deep learning detection framework, which combines the a novel YOLOv5 framework combined with a better-than-state-of-the-art

machine vision. Our revision broadens the spectrum of detection while improving the ability to detect small and subtle surface defects. In addition, the network provides a major contribution by not only pooling features from the three forward channels from the PANet (Path Agression Network) to the backbone network, but also with the use of a Dual Attention Mechanism. This additional feature increases the attentiveness

of the network in regard to high-value fine detail features related to small surface defects, and ultimately combats the common issue of conventional detection systems missing small or subtle defects. The efficacy of the proposed framework is validated through experimental results showing a remarkably high AP50 accuracy value of 97.3%, which was a 4.2% improvement over YOLOv5. Results indicate the robustness and adaptability of the system to inspections of load-bearing rail structure in an industrial surface inspection context.

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