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Advanced Deep Learning Models for Steel Defect Detection: YOLOv9, YOLOv8 & RT-DETR

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Abstract: *Steel defect detection is vital in ensuring product quality. This paper examines the application of advanced deep learning techniques on defect detection through Roboflow. This paper uses YOLOv9, a novel and most robust form of YOLO, in addition to other prominent models: YOLOv8 and RT-DETR. We continue an examination of the capabilities and limitations of these models in a steel defect identification context. It also describes its testing and study protocol on a customized defect detection data set. The findings of such a study are supported by our research, highlighting the optimal model while paying particular focus on Accuracy, speed, and identified defect types.*
Keywords: *Steel defect detection, Deep learning, YOLOv9, YOLOv8, RT-DETR.*

1. INTRODUCTION:

This includes factors that are of material characteristics and processing technologies in the industrial production process. This might cause inevitable influencing factors that may appear defects on the surfaces of metals and affect their qualities and subsequent application, hence great significance lies in the detection of surface defects to assure quality. General techniques used in an image processing technique to detect defects include localization of the defect, recognition of the defect and classification.

Buil for object detection applications under computer vision, it is the latest addition to the new line of the YOLO series, which has its latest release dated February 2024, YOLOv9[1]. It shall thus take over from RT-DETR [2] and the old YOLOv8 in what relates to speed, accuracy, and more importantly, scalability. All help in improving its performance can be credited to such things as the advancement in model architecture, developments in training techniques, and incorporation with new features such as GELAN and PGI. YOLOv8 provides one of the prominent deep learning architectures armed with one of the most advanced architectures and cutting-edge algorithms tailored to high-performance visual object tracking in real time. In fact, such models are really competing to the level that breakthroughs are made almost each day at very high speeds in modern computer vision and object detection.[3] These advancements hold immense potential for steel manufacturing, enabling more efficient and accurate defect detection, leading to improved product quality, reduced waste, and enhanced safety. As the field progresses, these models will play a pivotal role in automating and streamlining steel inspection processes, driving productivity and cost-effectiveness in the industry.
The primary aim of this project is to undertake a comprehensive analysis of NEU dataset by preprocessing it effectively by using Roboflow, followed by augmentation to expand the

dataset to 4116 images. Subsequently, training will be performed utilizing various advanced deep learning algorithms such as yolov9, yolov8, rt-detr with a focus on identifying the most suitable one for the task at hand. Through comparative analysis, deep learning algorithms will be evaluated to determine their effectiveness. This comparative assessment aims to provide insights into the strengths and weaknesses of different algorithms, ultimately facilitating the selection of the most efficient approach for the steel defect detection.

2.RELATED WORK:

Steel defect detection has seen remarkable advancements driven by the cutting-edge YOLO (You Only Look Once) series of object detection models. Its forerunner, YOLO was already a state-of-the-art deep learning model tailored for real-time detection of steel defects, boasting advanced algorithms and architectures. The rapid pace of innovation in computer vision and object detection is evident, with models evolving at breakneck speeds, continually pushing the boundaries.

Fatma.m.talaat developed the smart fire detection system(SFDS) leverages deep learning (YOLOv8) to identify fire-specific features in real-time for improved accuracy and lower false alarm[3].Yang Wang proposed an improved steel surface defect detection algorithm based on YOLOv7[4].Ling wang proposed a real-time steel surface defect detection system based on the YOLOv5 deep learning network[5].Yu He proposed An End-to-End Steel Surface Defect Detection Approach via Fusing Multiple Hierarchical Features using deep detection network [6]. Convolutional neural networks (CNN) have successfully implemented for metallic surface defect detection [7].designed a deep confidence network (DCN) for defect detection by Jonathan Masci [8]Xiaoming Lv proposed an active learning for Defects on metallic surfaces and explains how DCN (Deep Confidence Network), Faster-RCNN based methods, YOLO series (v1, v2, v3), and SSD (Single Shot MultiBox Detector) gives high accuracy when we have large no of data but it is computationally expensive, time consuming [9].For example, Ross Girshick developed a defect detection method based on Fast-RCNN [10] to detect five types of defects.

SSD offers a fast and accurate object detection approach using a single deep learning network, making it potentially valuable for real-time applications [11]. Jiaqiao Zhang proposed YOLOv3 for steel strip defect detection. The CP-YOLOv3-dense network offers good accuracy while maintaining efficient processing speed[12].Explains all YOLO models and their potential for industrial applications and CNN architectures for feature extraction (AlexNet, VGGNet, Google Net, ResNet) by muhammad hussain[13].The active learning for defect detection still faces large challenges. Compared with existing deep detection methods [14,15]. DCNN achieves better recognition accuracy compared to other DCNN models like VGGNet and Alex Net in steel defect detection [16]. An improved data augmentation for industrial defect classification with small-scale training datasets like NEU Dataset [17]. S.Kavitha proposed improvised YOLOv5 for steel surface defect detection. They address challenges like small defects and achieve higher accuracy with modifications like adding attention layers and using a specific loss function.[18]

3.METHODS:

3.1. YOLOv9 Model:

YOLOv9, released in February 2024, is to revolutionize steel defect detection. This cutting -edge object detection model boasts significant improvements in speed, accuracy, and most importantly, scalability – all crucial factors for real-world industrial applications. YOLOv9 surpasses previous techniques like RT-DETR and even its predecessor

Key features:

1.Revamped Architecture: The underlying structure of the model has been significantly improved, specifically designed to excel at steel defect detection tasks.

2.Optimized Training: Training techniques have been honed to ensure YOLOv9 can effectively learn and identify even the most subtle defects.

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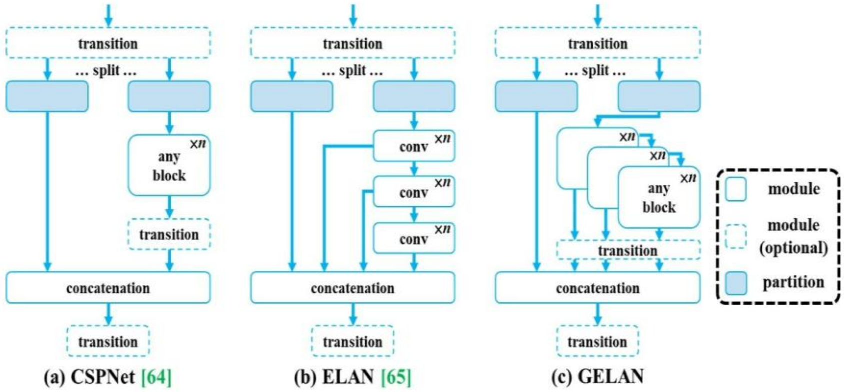

Fig.1. YOLO v9 architecture

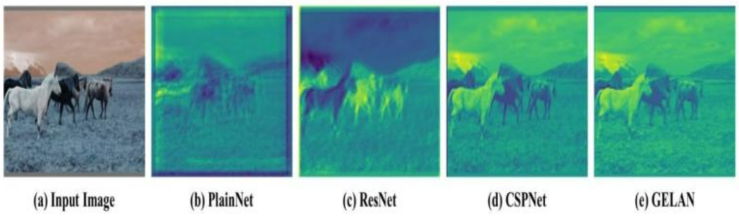

Fig.2. YOLO v9 architecture

Powerful New Features: The inclusion of groundbreaking features like GELAN (Generalized Efficient Layer Aggregation Network) and PGI (Programmable Gradient Information) further enhances YOLOv9's ability to pinpoint defects with exceptional precision.

With its superior speed and accuracy, YOLOv9 promises to streamline steel production lines by enabling real-time defect detection.

3.2. RT-DETR Model:

The first real-time end-to-end object detector based on transformers.
Key features:

1.Efficient Hybrid Encoder: This component efficiently processes features from different scales by separating interactions within a scale from interactions between scales, making it suitable for complex tasks like steel defect detection where defects can vary in size and appearance.

2.IoU-aware Query Selection: This method improves the initialization of object queries, leading to better detection of steel defects.

3.Flexible Decoder Layers: By employing various decoder layers, the model permits adjustment of inference speed without retraining, thereby rendering it more applicable in real-world situations.

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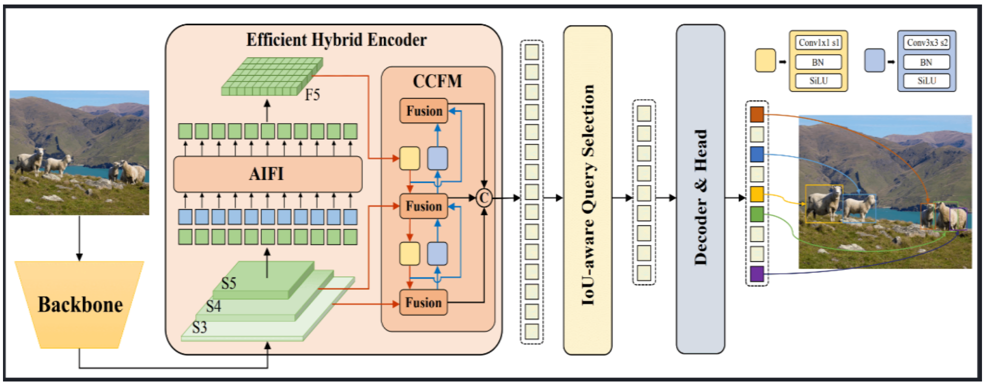

Fig.3. RT-DETR architecture

3.3. YOLOv8 Model:

Key Features:

YOLOv8's Strengths for Steel Defect Detection:

1. Advanced Architectures: YOLOv8's backbone and neck architectures are designed for efficient feature extraction, which is crucial for identifying subtle defects on steel surfaces.

2. Anchor-Free Design: Unlike anchor-based approaches, YOLOv8 predicts object centers directly, potentially leading to better accuracy for irregular defective shapes.

3. Speed and Pre-trained Models: Real-time capabilities and a variety of pre-trained models make YOLOv8 a good candidate for industrial applications like steel defect detection.

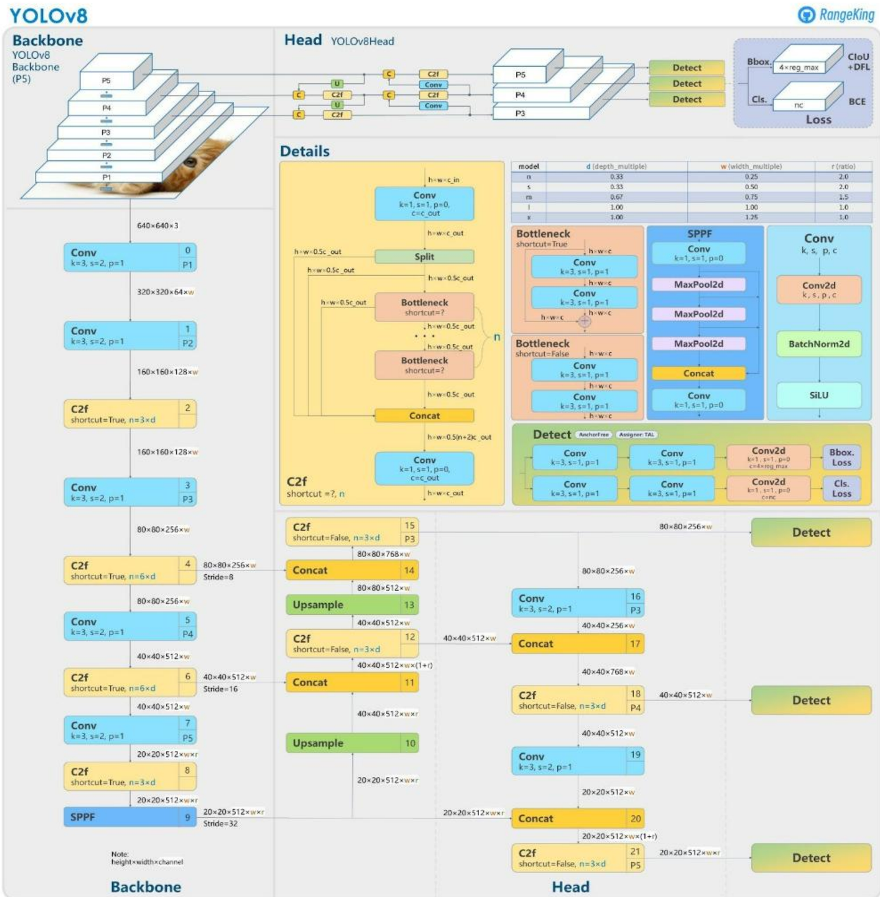

Fig.4.YOLO v8 architecture

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4.DATA PROCESSING:

NEU-Dataset Process consists of 3 steps which are data collection, data preprocessing, data augmentation by using Roboflow tools.

4.1. Data collection:

The dataset is taken from Kaggle. It is already preprocessed data. The data is again processed using Roboflow tools for further enriching the dataset.

4.2. Data preprocessing:

Preprocessing ensured uniformity: auto-orientation aligned images, resizing to 640x640 standardized dimensions. Crucial for accuracy, minimizing biases, and establishing reliability in subsequent analysis. Facilitates comprehensive exploration and robust conclusions.

4.3. Data augmentation:

Through data augmentation, the dataset size was enriched from 1799 to 4116 images. This process involved techniques such as rotation (90° Rotate: Clockwise, Counter-Clockwise), flipping(horizontal) to introduce diverse variations, thereby reducing overfitting risks and enhancing the model's ability to generalize.

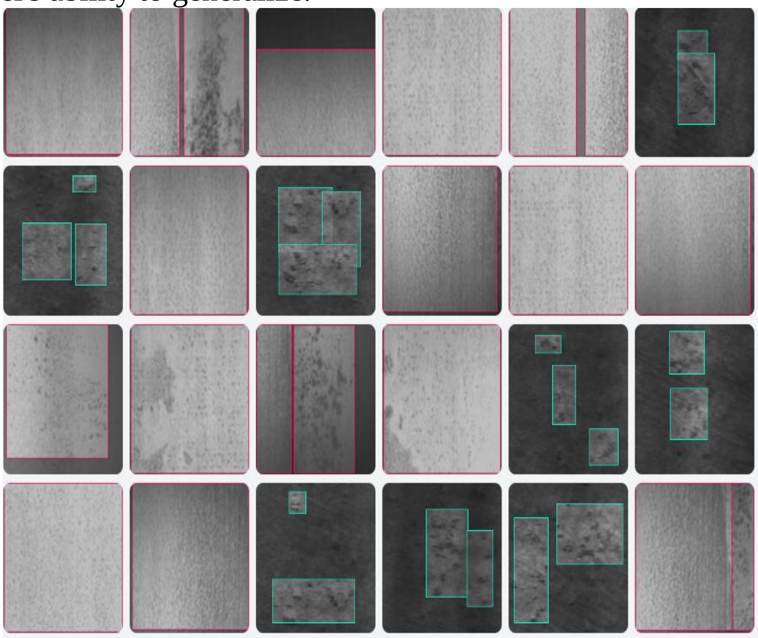

Figure-5

The augmentation significantly increased the dataset's size, providing a richer and more diverseset of examples for training, ultimately improving the robustness and effectiveness of the model in recognizing steel defects.

5.RESULTS:

This Dataset consists of 6 types of steel defect features such as crazing, inclusion, patches, pitted surface, rolled-in scale, scratches are trained for EPOCH 25,50 on deep learning models.

In table 1, we have trained the deep learning algorithms for 25 epoch and rt-detr achieved 0.741 mAP slightly better than yolo v8 0.739 mAP and outperformed yolo v9 0.729 mAP.

In table 2, we have trained the deep learning algorithms for 50 epoch and yolov9 achieved 0.759 mAP slightly better than yolo v8 0.749 mAP and outperformed rt-detr 0.661 mAP.

	YOLOv9			YOLOv8-l			RT-Detr-l		
Class	P	R	mAP-50	P	R	mAP-50	P	R	mAP-50
All	0.698	0.661	0.729	0.683	0.709	0.739	0.717	0.704	0.741
Crazing	0.535	0.282	0.434	0.56	0.359	0.439	0.399	0.465	0.377
Inclusion	0.607	0.667	0.701	0.549	0.77	0.703	0.682	0.695	0.713
Patches	0.838	0.926	0.954	0.804	0.91	0.941	0.883	0.938	0.948
Pitted_surface	0.866	0.713	0.813	0.9	0.775	0.876	0.961	0.619	0.873
Rolled-in-scale	0.553	0.462	0.543	0.55	0.542	0.553	0.552	0.613	0.595
scratches	0.79	0.915	0.931	0.731	0.897	0.921	0.824	0.897	0.942

TABLE-1

TABLE-2

	YOLOv9			YOLOv8-l			RT-Detr-l		
Class	P	R	mAP-50	P	R	mAP-50	P	R	mAP-50
All	0.757	0.684	0.759	0.678	0.717	0.749	0.601	0.615	0.661
Crazing	0.597	0.282	0.455	0.473	0.387	0.427	0.284	0.261	0.211
Inclusion	0.698	0.723	0.736	0.61	0.752	0.722	0.489	0.745	0.693
Patches	0.893	0.873	0.949	0.843	0.914	0.946	0.82	0.889	0.924
Pitted_surface	0.884	0.762	0.878	0.847	0.692	0.875	0.749	0.374	0.686
Rolled-in-scale	0.626	0.535	0.577	0.507	0.641	0.591	0.509	0.549	0.56
Scratches	0.843	0.932	0.961	0.79	0.915	0.934	0.755	0.872	0.891

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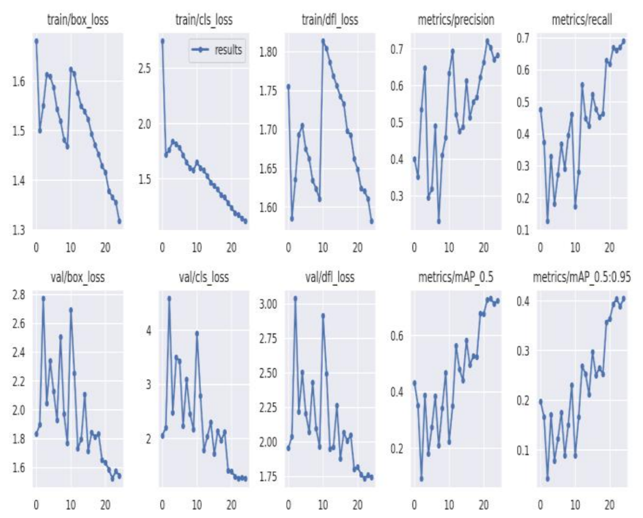
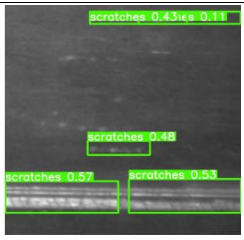
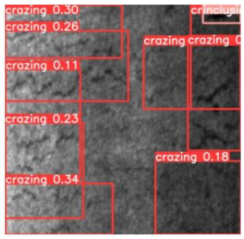
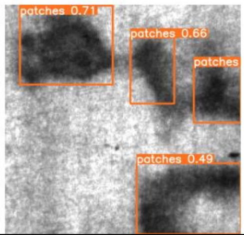
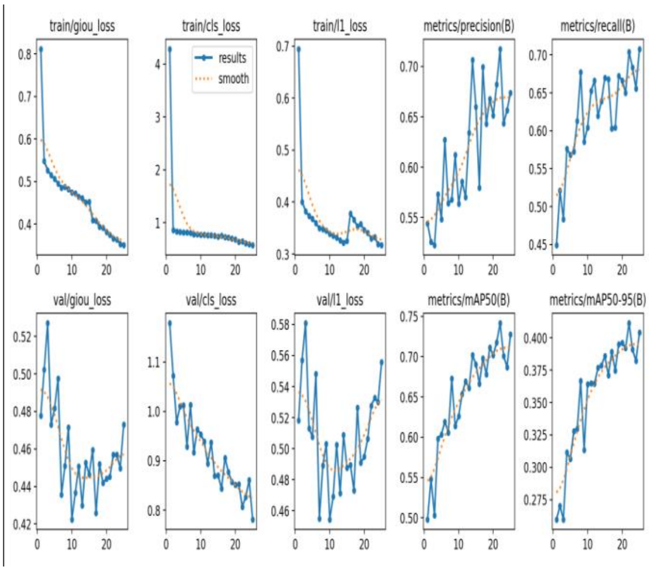
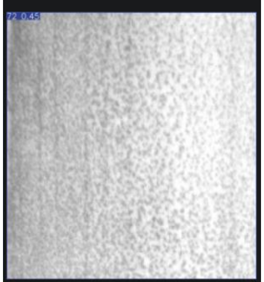
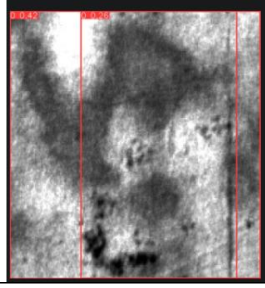
Paper: 36

TABLE-3 GRAPHS & PREDICTIONS

Algorithms	Epoch	Results	Prediction
YOLOv9	25		  
RT-detr-large	25		  

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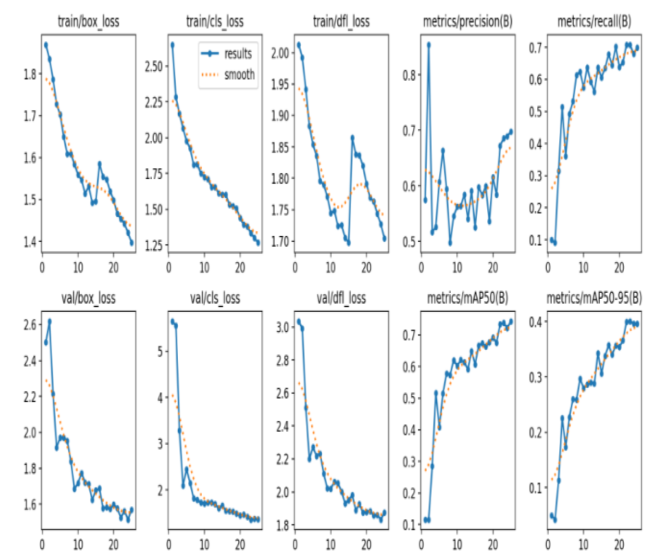
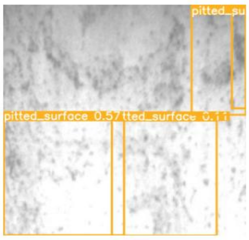
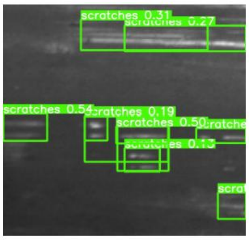
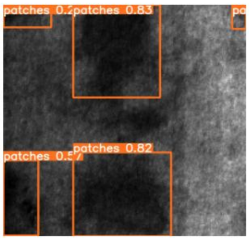
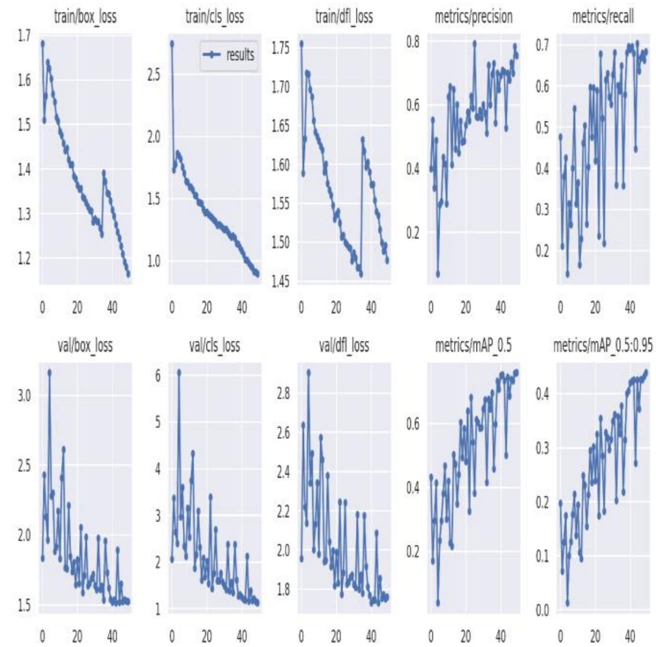
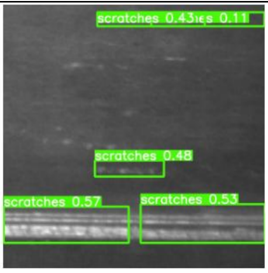
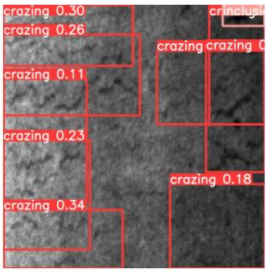
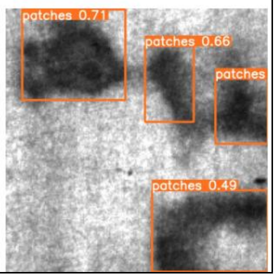
YOLOv 8-large	25		  
YOLOv 9	50		  

Journal of Current Research in Engineering and Science

JCRES

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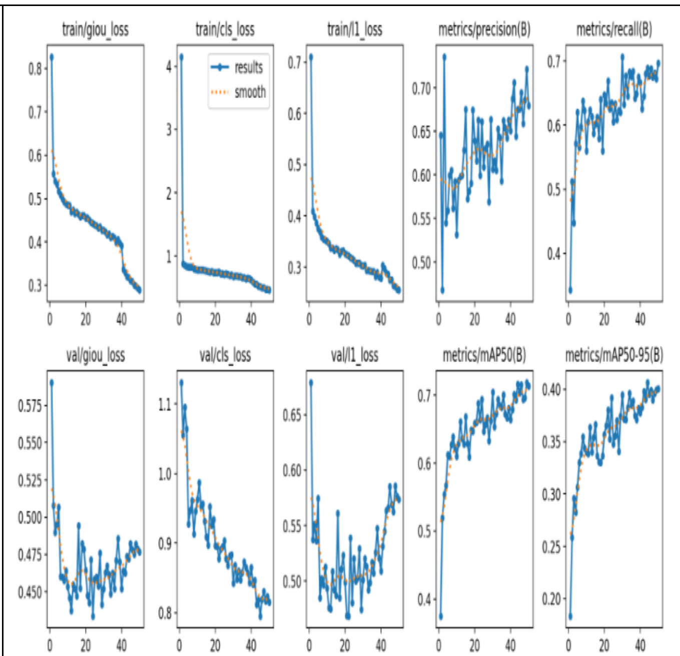
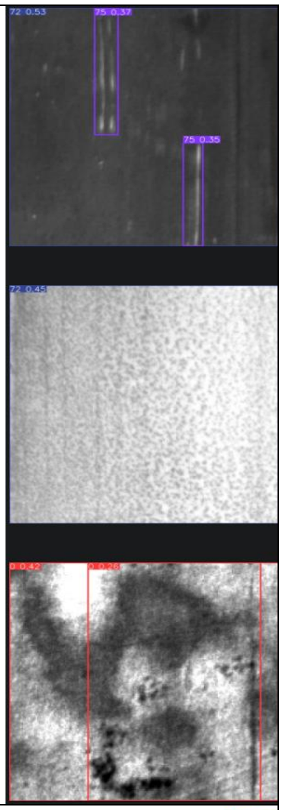
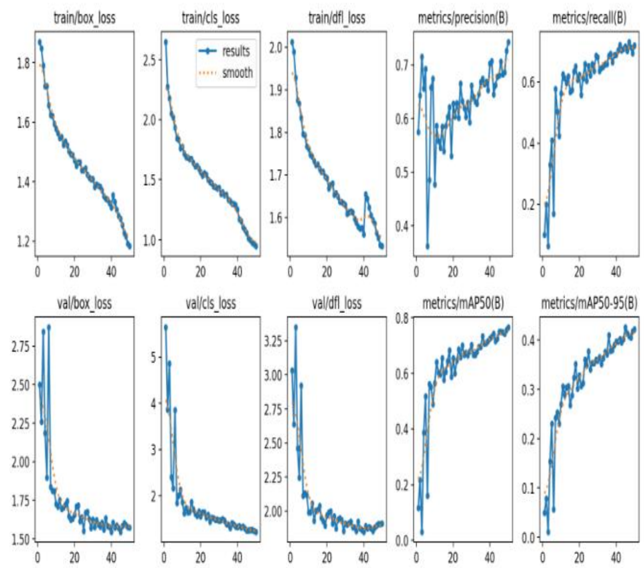
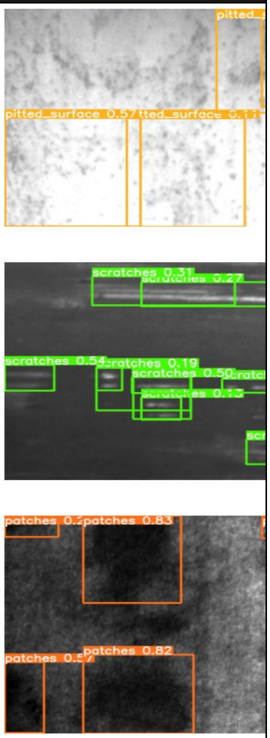
Paper: 36

RT-detr-large	50		
YOLOv8-large	50		

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Journal of Current Research in Engineering and Science
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Paper: 36

6.CONCLUSION:

Overall, the YOLOv9 achieves the highest mAP, signifying its ability to accurately detect a broader range of steel defects compared to RT-DETR-large and YOLOv8 large.
1.YOLOv9 for Superior Accuracy: After 50 epochs of training, YOLOv9 achieved the slightly superior mean Average Precision (mAP) of 0.759, indicating its superior ability to accurately detect a wider range of steel defects compared to RT-DETR (0.661 mAP) and YOLOv8 (0.749 mAP). This enhanced accuracy is crucial for reliable steel defect detection.

2.RT-DETR Performance: While exhibiting a promising start at 25 epochs, RT-DETR's performance dropped at 50 epochs, suggesting potential overfitting or requiring further hyperparameter tuning for this specific dataset.

3.YOLOv9 Efficiency Advantage: While traditionally transformer-based models can be computationally expensive, YOLOv9, despite its recent release, surpasses YOLOv8, a well-established model, potentially offering a balance between accuracy and computational efficiency. This efficiency is critical for real-time applications where speed is essential.

Given YOLOv9's promising initial performance, we expect further advancements in its accuracy and speed through ongoing development. This has the potential to make YOLOv9 an even more robust choice for steel defect detection and other industrial applications where both speed and accuracy are vital.

7.ACKNOWLEDGMENT:

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