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LEVERAGING DEEP LEARNING MODELS FOR WELDING DEFECT DETECTION

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Abstract

The traditional methods used for weld defect detection are time-consuming and require a high level of expertise. This study aims to evaluate the performance of three deep learning algorithms - YOLOv8, DETR, and Detectron - on weld defect detection. Deep learning techniques have shown great potential in detecting weld defects. The study will use a dataset of images of welded structures with defects and will train the models using transfer learning techniques. The performance of the models will be evaluated using various metrics such as precision, recall, F1-score, and mean average precision (mAP). The results of the study will contribute to the development of more accurate and efficient methods for weld defect detection in the manufacturing industry. The study will also compare the strengths and weaknesses of each algorithm and identify the most suitable algorithm for detecting weld defects.

Keywords: You Only Look Once (YOLO), DEtection Transformer (DETR), mean average precision(mAP), Region-Based Convolutional Neural Network (R-CNN), Object Detection.

I. Introduction

Welding is a critical process in manufacturing and construction industries, as it joins materials together to create strong and reliable structures. However, welding defects can compromise the integrity of these structures, leading to safety hazards, operational issues, and costly repairs. Traditional methods of detecting weld defects, such as visual inspection and ultrasonic testing, are time-consuming, labour-intensive, and may miss subtle defects. Fortunately, advances in deep learning techniques have revolutionized the field of weld defect detection. Deep learning algorithms can learn to recognize complex patterns in weld images and classify them as acceptable or defective with high accuracy. Moreover, they can detect defects that may be difficult or impossible for humans to see. Welding is a critical process in manufacturing and construction industries as it joins materials together to create strong and reliable structures. However, welding defects can compromise the integrity of these structures, leading to safety hazards, operational issues, and costly repairs. Some of the common types of welding defects include porosity, undercutting, incomplete fusion, and cracks. This study is an overview of the state-of-the-art techniques for weld defect detection using deep learning. The challenges in detecting weld defects, the different types of defects, the datasets used for training and testing, and the various deep learning architectures that have been employed are discussed later on. This study highly focuses on how deep learning can improve the accuracy and efficiency of weld defect detection, and how it can enhance the safety and reliability of welded structures.

1.1 Welding & Welding Defects

Welding is a manufacturing process that involves joining two or more pieces of metal together using heat and/or pressure. It is widely used in various industries, including construction, automotive, aerospace, and shipbuilding, among others. Welding is essential for creating strong, durable, and reliable structures and components.

However, welding can also lead to defects and imperfections, which can compromise the quality and safety of welded structures. Welding defects can occur due to a variety of factors, including improper welding techniques, poor quality of welding materials, incorrect welding parameters, and inadequate inspection and testing procedures.

Some of the common welding defects include:

- Porosity: A condition where gas pockets or voids are trapped inside the weld metal, which can weaken the weld and reduce its mechanical properties.
- Cracks: A fracture or discontinuity in the weld metal or heat-affected zone, which can lead to failure or breakage under stress.
- Incomplete fusion or penetration: A condition where the weld metal does not completely fuse or penetrate the base metal, resulting in a weak and incomplete joint.
- Undercut: A groove or depression along the edges of the weld metal, which can reduce the thickness and strength of the joint.
- Spatter: A condition where small droplets of molten metal are ejected from the welding arc, which can cause surface imperfections and reduce the aesthetic appearance of the weld.

Detecting and addressing welding defects is critical for ensuring the safety and reliability of welded structures. Various inspection and testing techniques, including visual inspection, radiography, ultrasonic testing, and magnetic particle inspection, are commonly used to identify welding defects. Additionally, advancements in machine learning and computer vision have enabled the development of automated welding defect detection systems that can analyse images of welds and identify defects with high accuracy and speed.

1.2 Object Detection

Object detection is a computer vision technique that involves identifying and localizing objects of interest within an image or video. It is a crucial task in various applications, including surveillance, robotics, autonomous vehicles, and manufacturing, among others. Object detection can be achieved using different approaches, including traditional computer vision techniques and deep learning methods.

In the context of weld defect detection, object detection can be used to identify and classify different types of welding defects within an image of a welded structure. This approach involves training a deep learning model on a large dataset of labelled images, where each image is annotated with the location and type of welding defect present.

There are various deep learning-based object detection models that can be used for weld defect detection, including the Detection Transformer (DETR), the You Only Look Once (YOLO) model, and the Faster R-CNN model, among others. These models can be fine-tuned and adapted to the specific needs of the weld defect detection application, such as the size and shape of the defects, the lighting and environmental conditions, and the type of welding process used.

Object detection can improve the efficiency and accuracy of weld defect detection, reducing the need for manual inspection and testing, and enabling real-time monitoring and analysis of welding processes. However, object detection models require large amounts of labelled data for training, which can be time-consuming and expensive to collect. Additionally, the performance of object detection models can be affected by various factors, such as occlusion, scale, and orientation of the objects, which can make the detection process challenging in some cases.

II. Literature Review

2.1 Automatic technologies for weld defect detection based on digital radiographic images[1]

Digital radiography has become a widely accepted method for detecting weld defects due to its high accuracy and efficiency. These systems mainly involve several technologies such as image pre-processing, defect segmentation, feature extraction and selection, classification. Image pre-processing techniques are used to enhance the quality of the digital radiographic images. Defect segmentation techniques are used to segment the weld region from the background and the defect region from the weld region. Feature extraction and selection techniques are used to extract the relevant features from the segmented defect region. Finally, classification techniques are used to classify the defect type.

2.2 Detecting and classifying welding defects using geometric features[2]

Geometric features such as width, height, and length can be used to detect and classify welding defects. These features are extracted from the weld image and fed into a machine learning algorithm to classify the defect type. This method is effective in detecting defects such as cracks, lack of fusion, and porosity.

2.3 Rapid detection of distortions formed in the welds of metal[3]

Various types of surface defect detection techniques have found that rapid detection of distortions formed in the welds of metal has high importance to prevent disasters. These techniques involve detecting and analyzing changes in the shape and geometry of the weld. This method is effective in detecting defects such as distortions, buckling, and warping.

2.4 X- Ray weld Inspection[4]

X-ray weld inspection is another common method that can be used to detect internal weld defects that are not visible to the naked eye. X-ray images are taken of the weld and analyzed for defects such as porosity, lack of fusion, and cracks. This method is particularly useful in detecting internal defects that are not visible on the surface of the weld.

2.5 Convolutional Neural Network (CNN) for weld surface image classification[5],[9]

Convolutional Neural Network (CNN) is one of the core algorithms used in machine vision for weld surface image classification. CNNs are particularly effective in detecting features and patterns in images. In the context of weld surface image classification, CNNs can be used to classify the defect type based on the features extracted from the weld image.

2.6 Visual inspection for weld defect detection[6]

Visual inspection is one of the most cost-effective and basic non-destructive welding inspection types. It involves visually examining the surface of the weld for defects such as cracks, incomplete fusion, and other defects. This method is particularly effective in detecting defects that are visible on the surface of the weld.

2.7 AF-RCNN object detection framework for X-ray weld defect detection[7]

In another study, an AF-RCNN object detection framework was proposed for X-ray weld defect detection. This framework includes an attention mechanism because defect images have too many small defects, and feature information of small defects is more likely to be missing during the convolution. The proposed method showed promising results in detecting and localizing defects in X-ray images of welds.

The proposed methods don’t directly deal with RGB scale images but rather they are more focused on X-ray and radiographic images. Also, there is no direct evidence that other than conventional CNNs no state-of-the-art models are used or fine-tuned for the data of weld defects. The following proposal focuses on using Deep Learning algorithms on labelled weld defects data and train the models on them to get better accuracies and further can be deployed in real-time applications.

III. Methodology

3.1 The Dataset

The dataset for this project consists of labelled images, divided into three categories: train, test, and validation. The train data is used for training the deep learning models, while the test

data is used to evaluate the performance of the trained models. The validation data is used to monitor the training process and prevent overfitting.
Each of the three categories contains two sub-folders: images and labels. The images folder contains the raw image files, while the labels folder contains the corresponding annotations for each image in a specific format. The annotations include information about the workpiece, welding line, and any welding defects present, such as incomplete fusion, spatter, or porosity.
The workpiece and welding line annotations provide context for the image and allow the deep learning models to differentiate between different types of welds and welding processes. The welding defect annotations provide information about the location and type of welding defect present in the image, allowing the deep learning models to identify and classify the defects accurately.
Overall, the dataset structure provides a consistent and organized way of storing the labelled images and annotations, allowing for easy access and manipulation during the training and testing phases of the project.

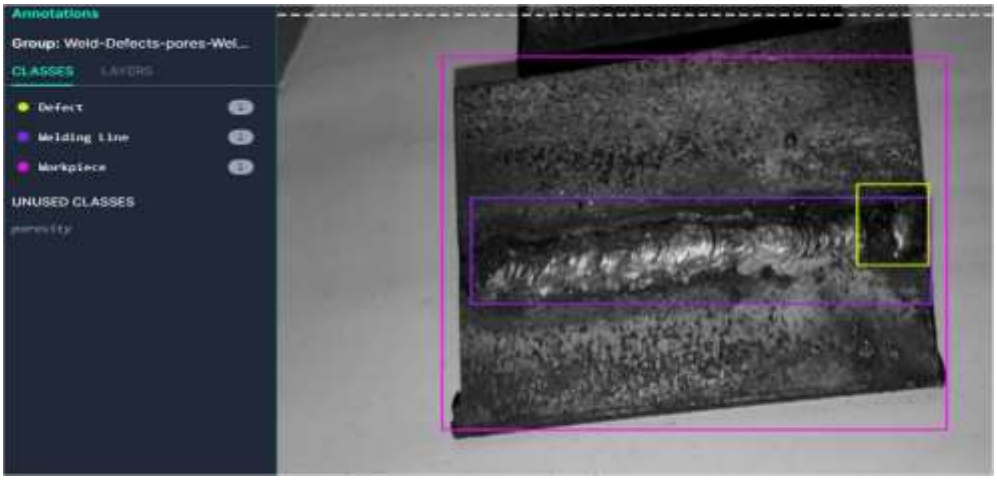

Fig 1: (Gray Scale) Image showing the defect in welding line[11].

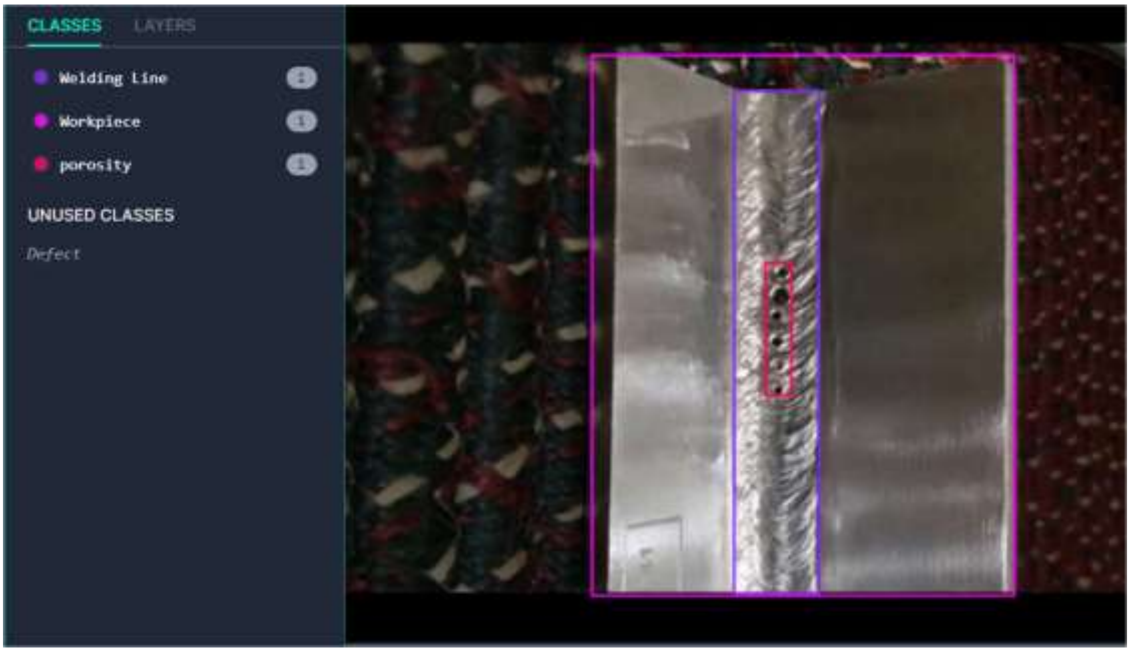

Fig 2: Image showing the porosity in the welding line[12].

3.2 Data Pre-Processing and Identifying the Process Parameters

Although there are some studies which suggest detection of weld defects in metal materials based on surface texture analysis [8], they are not clearly differentiating the types of materials and welds. The following are some pre-processing techniques that are followed before implementation of models:

- Image Resizing: Resizing the image to a specific size can help in reducing the memory requirement and computational time while processing the image.
- Image Normalization: It involves converting the pixel values of the image to a standard scale or range, which can be helpful for reducing the effect of lighting conditions, improving image contrast, and making images more suitable for machine learning algorithms.
- Image Augmentation: It is a process of generating new images from the existing dataset by applying transformations such as rotation, flipping, zooming, and shifting. It can help in increasing the diversity of the dataset and improving the performance of machine learning models.

In addition to the labelled images and annotations, the dataset for this project also includes information about the process parameters used during the welding process. The process parameters refer to the various settings and conditions involved in the welding process, such as the welding speed, voltage, and current. These parameters can have a significant impact on the quality of the weld and the occurrence of welding defects. By including information about the process parameters in the dataset, understanding the relationship between these parameters and the occurrence of defects will be better. This can help to develop more accurate and reliable deep learning models for weld defect detection. In this section, the process of identifying and extracting the process parameters from the dataset, and how this information in the development of our deep learning models is discussed.

- Image resolution: The resolution of the images can impact the quality of the data being analyzed and may need to be optimized for the specific requirements.
- Image color: The color of the images can affect the appearance of the defects and may need to be considered in the data analysis.
- Image background: The background of the images can impact the appearance of the defects and may need to be standardized.
- Image orientation: The orientation of the images (e.g. horizontal, vertical, etc.) can affect the appearance of the defects and may need to be standardized for the project.

Fig 3: Images showing different orientations

- Welding material: The type of the material may also affect the appearance of the defects. The dataset widely contains defects in Mild Steel.
- Type of joint: The dataset widely contains the defects in butt joint and corner joint.

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Fig 4(A): Image showing the porosity in corner joint


Fig 4(B): Image showing spatter in butt joint

3.3 Selection of Object Detection Models

After conducting a thorough review of the literature and evaluating the performance of several models, a model from each of its own category has been selected: DETR, Detectron, and YOLOv8

The DETR model is a state-of-the-art object detection model that uses a transformer-based architecture to detect objects in an image. It is known for its high accuracy and efficiency and has been shown to outperform other object detection models on various benchmarks.

The model predicts a set of object queries instead of bounding boxes, paired with positional encodings and uses bipartite matching. During training, the model minimizes a joint loss function to balance classification and localization objectives and encourage query diversity. DETR can also be used for instance segmentation by predicting a mask for each object query.

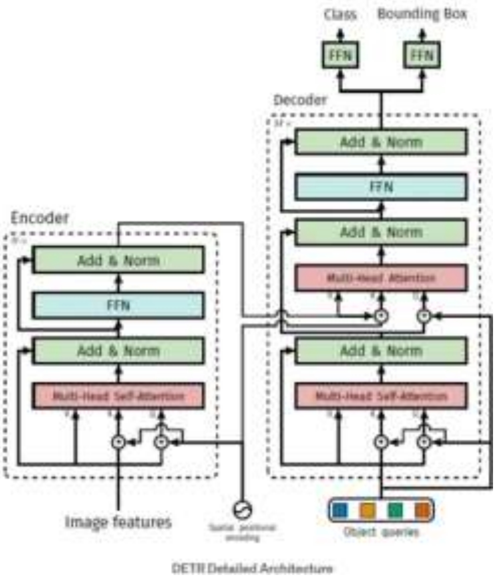

Fig 5: Architecture of Detection Transformer

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The complete implementation of DETR Model is available *here*.

The Detectron model is another popular object detection model, developed by Facebook AI Research. It uses a region-based convolutional neural network (R-CNN) to detect objects in an image and has achieved state-of-the-art results on various object detection benchmarks. The model is based on a Mask R-CNN architecture, which is a two-stage object detection framework that can detect objects and their pixel-level segmentation simultaneously. A study suggests that usage of R-CNN architecture can be useful for weld defects [10], it is included here to test the performance of the R-CNN against other models. The framework is highly modular and customizable, making it easy to use and adapt for different applications.

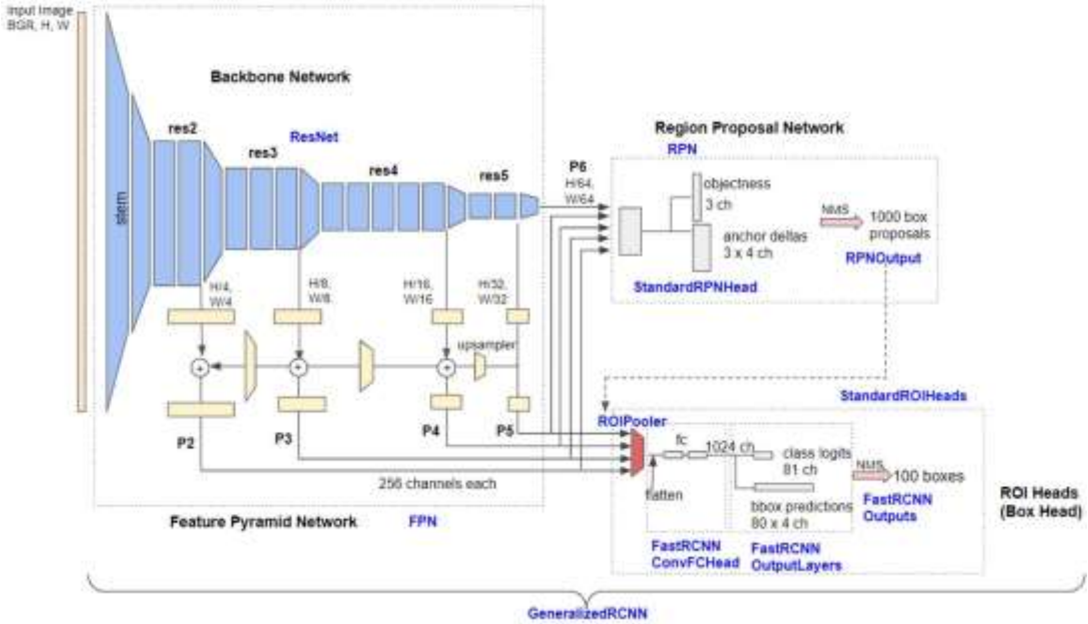

Fig 6: Architecture of Detectron The complete implementation of Detectron is available *here*.

Finally, YOLOv8 (You Only Look Once version 8) is a real-time object detection model that uses a single neural network to predict bounding boxes and class probabilities for objects in an image. It has been shown to achieve high accuracy and fast processing times, making it a popular choice for real-time applications.

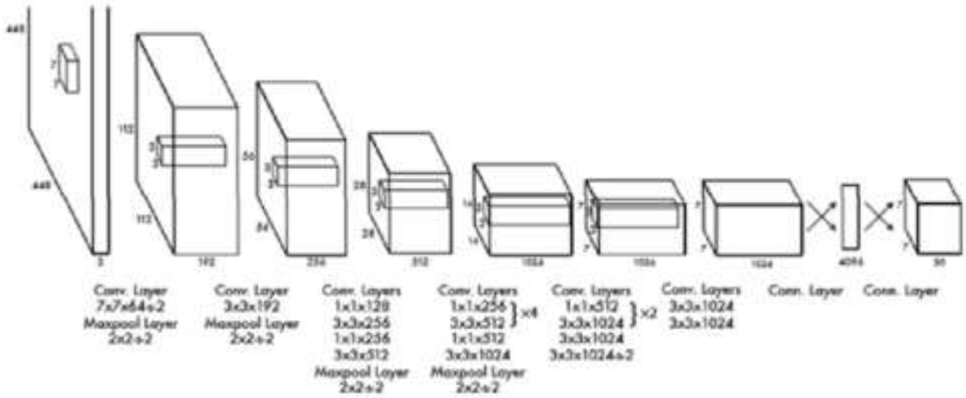

Fig 7: Architecture of YOLO V8

By selecting these three models for testing, this study aims to determine which model is most suitable for detecting welding defects in our dataset. Each model has its unique strengths and weaknesses, their performance based on various metrics, such as accuracy are evaluated. This will allow us to select the best model for our weld defect detection system, ensuring that it is accurate, efficient, and effective in detecting welding defects.

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The complete implementation of YOLO is available *here*

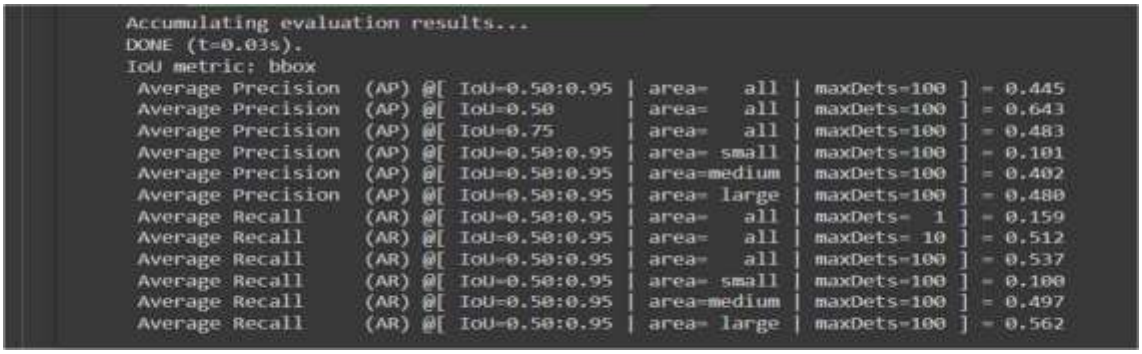
IV. Results

4.1 Metrics for Detection Models

There are several metrics used to evaluate the performance of object detection models. Some of the commonly used metrics include:

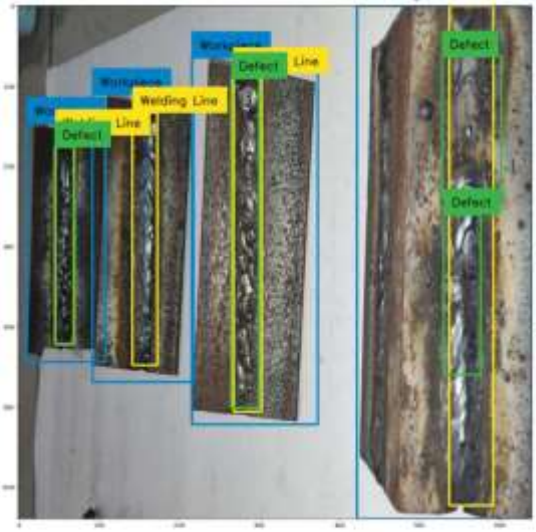
- Precision: The proportion of predicted bounding boxes that correctly match the ground truth bounding boxes.
- Recall: The proportion of ground truth bounding boxes that are correctly identified by the model.
- Average Precision (AP): The average precision across different recall values.
- Intersection over Union (IoU): A measure of the overlap between the predicted bounding box and the ground truth bounding box.
- Mean Average Precision (mAP): The average AP across different classes. mAP is often reported at different levels of IoU, such as mAP50 and mAP90. These metrics represent the mean average precision at an IoU threshold of 0.5 and 0.9, respectively. An IoU threshold of 0.5 means that the predicted bounding box is considered a true positive if it overlaps with the ground truth bounding box by at least 50%, while an IoU threshold of 0.9 requires a higher degree of overlap for the predicted bounding box to be considered a true positive.

4.2 Testing the DETR Model



```
Accumulating evaluation results...
DONE (t=0.03s).
IoU metric: bbox
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.445
 Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.643
 Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.483
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.101
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.402
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.480
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.159
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.512
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.537
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.100
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.497
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.562
```

Fig 8: Performance of DETR Model



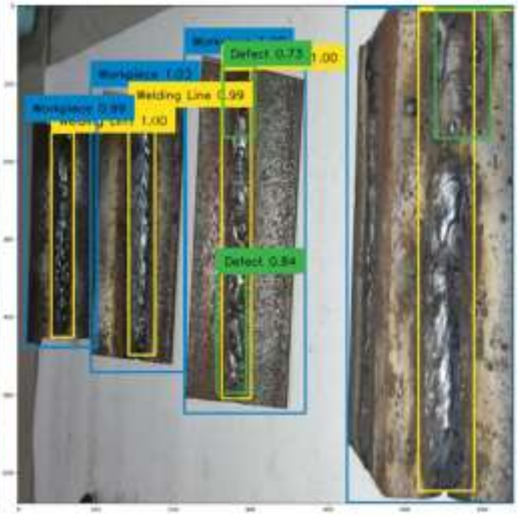


Fig 9(A): Original Image from Dataset Fig 9(B): DETR predicted Image

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4.3 Testing the Detectron Model

```
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.509
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.172
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.554
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.603
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.067
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.599
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.634
[04/27 07:51:35 d2.evaluation.coco_evaluation]: Evaluation results for bbox:
|   AP   |  AP50  |  AP75  |  APs  |  APm   |  APl   |
|:------:|:------:|:------:|:-----:|:------:|:------:|
| 50.200 | 75.239 | 51.211 | 0.612 | 51.458 | 50.885 |
[04/27 07:51:35 d2.evaluation.coco_evaluation]: Per-category bbox AP:
| category                         | AP     | category   | AP     | category     | AP     |
|:---------------------------------|:-------|:-----------|:-------|:-------------|:-------|
| Weld-Defects-pores-Weld-Defects  | nan    | Defect     | 10.753 | Welding Line | 55.748 |
| Workpiece                        | 84.099 | porosity   | nan    |              |        |
OrderedDict([('bbox',
              {'AP': 50.19981286669659,
               'AP50': 75.2394023752951,
               'AP75': 51.2109048550226,
               'APs': 0.6120612061206122,
               'APm': 51.45750022346607,
               'APl': 50.88477176997669,
               'AP-Weld-Defects-pores-Weld-Defects': nan,
               'AP-Defect': 10.753039417854236,
               'AP-Welding Line': 55.747720245760114,
               'AP-Workpiece': 84.09867893647541,
               'AP-porosity': nan})])
```

Fig 10: Performance of Detectron Model

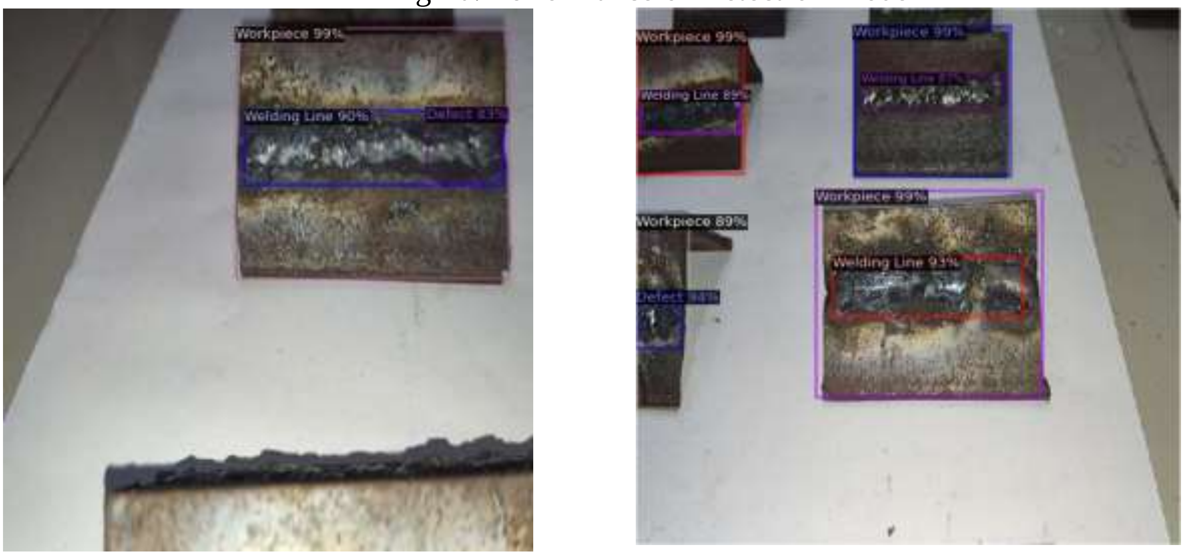

Fig 11: Test Results of Detectron Model

4.4 Testing the YOLO Model

Class	Images	Instances	Box(P	R	mAP50	m
all	116	773	0.838	0.89	0.868	0.659
Defect	116	131	0.536	0.6	0.517	0.239
Welding Line	116	294	0.935	0.966	0.971	0.702
Workpiece	116	307	0.922	0.993	0.988	0.918
porosity	116	41	0.961	1	0.995	0.779

Fig 12 : Performance of YOLO V8 model

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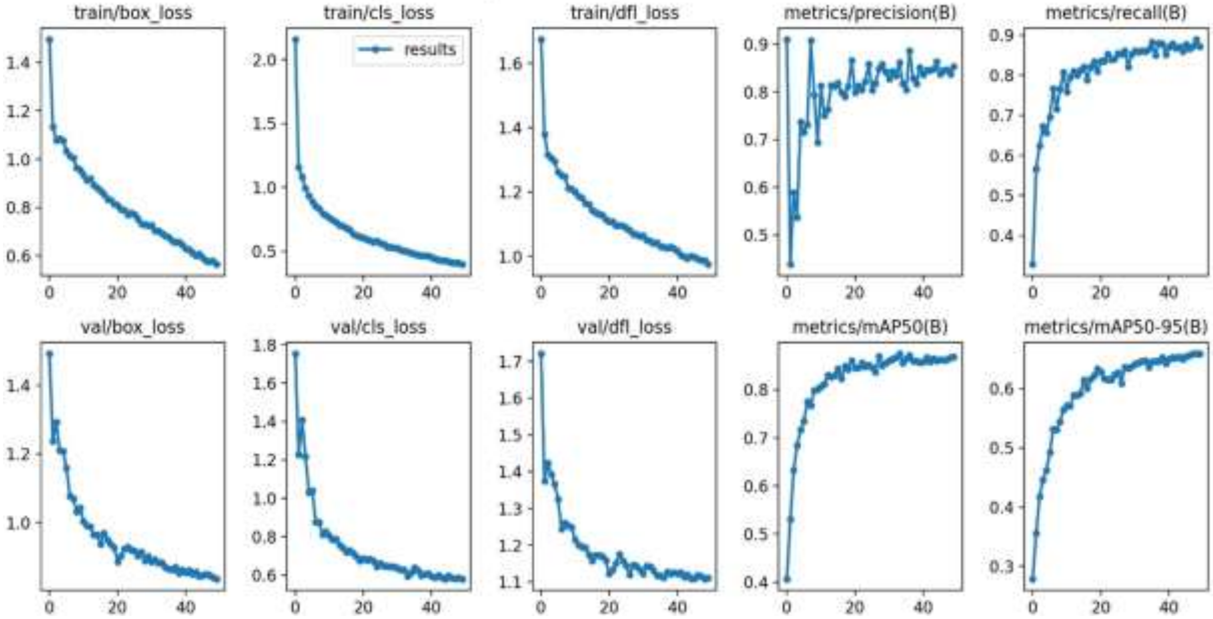

Fig 13: Training and Validation Graphs of YOLO

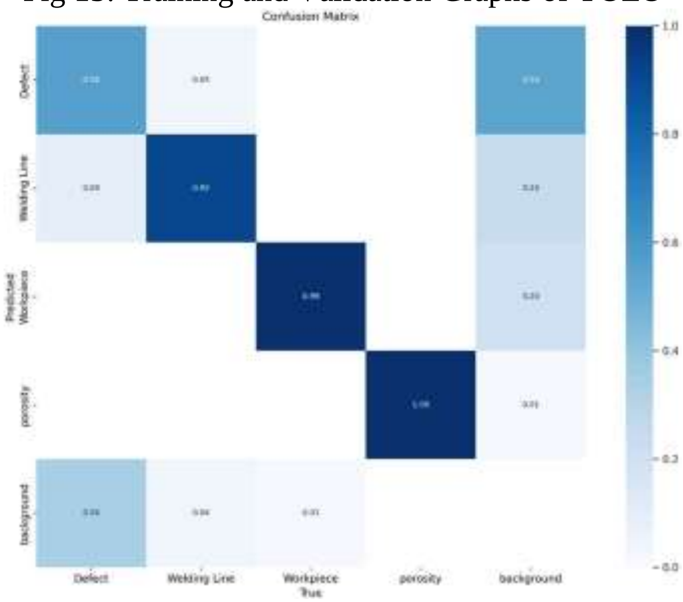

Fig 14: Confusion Matrix – Checking the Correlation between Process Parameters

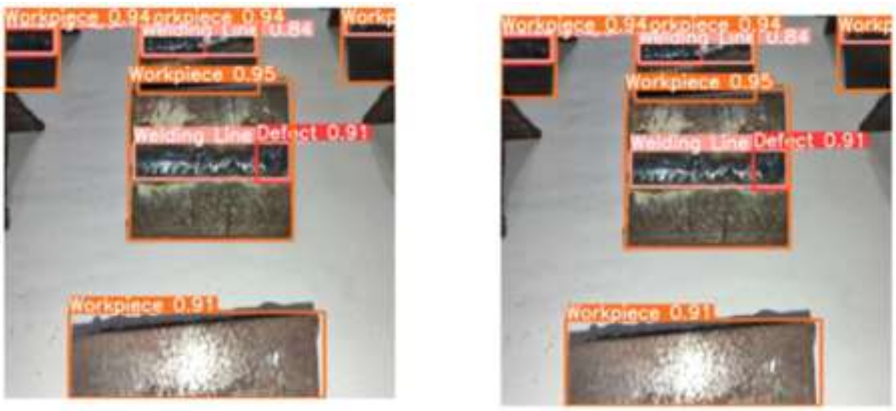

Fig15: Test Results of YOLO

4.5 Comparison of Results

S.No	Parameter	DETR	Detectron	YOLO
1	Work Piece	0.480	0.4099	0.988
2	Weld Line	0.643	0.55548	0.971
3	Defect (Incomplete fusion / Spatter)	0.101	0.10753	0.517
4	Porosity	0.402	(Not Included)	0.995

Table 1: Comparison of Average Precision of predicted Bounding Box

V. Conclusion

5.1 Summary

The objective of this study was to explore the application of deep learning for weld defect detection using object detection models, specifically DETR, Detectron, and YOLOv8. The report discussed the background of welding and welding defects, deep learning, and object detection. The dataset used for training and testing the models contained labelled images of workpieces, welding lines, and different types of defects.

The methodology section explained the flow of the project, including data pre-processing, identifying process parameters, and selecting object detection models. Three models, DETR, Detectron, and YOLOv8, were used for implementing the project.

The results and discussion section presented the testing of all three models, and the comparison of their results. The results showed that YOLOv8 outperformed the other two models, with an mAP90 score of 0.659 and an mAP50 score of 0.86, indicating a high degree of accuracy in detecting objects with significant overlap with the ground truth bounding boxes.

In conclusion, the study showed that deep learning and object detection can be successfully applied to weld defect detection. Among the three object detection models evaluated, YOLOv8 demonstrated the highest performance in terms of accuracy and precision. This report provides a foundation for future research on the application of deep learning in weld defect detection and related manufacturing processes.

5.2 Future work

The present study has demonstrated the effectiveness of deep learning and object detection for weld defect detection. However, there is still scope for future research in this area.

Firstly, a larger and more diverse dataset could be collected to improve the accuracy and robustness of the models. More types of defects could be added to the dataset to train and test the models more comprehensively.

Moreover, the study could be extended to include real-time detection of weld defects. This could be achieved by developing a real-time system that integrates with the welding process and provides feedback to the operator in real-time.

Also, the study could be expanded to include defect classification, which would involve distinguishing between different types of defects and providing appropriate corrective actions.

Finally, the study could be extended to include other manufacturing processes, such as casting and machining, to explore the potential of deep learning and object detection in detecting defects in a broader range of manufacturing processes.

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