

Application of YOLOv8 in fusion welding defect detection on carbon steel for potential remote visual inspection

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ABSTRACT

Nowadays, deep learning and machine vision technologies are power artificial intelligence tools based on industrial welding defect detection operations in manufacturing and require superior automated inspection systems. YOLOv8 represents the advanced stage of YOLO deep neural network architecture which brings powerful object detection features to fusion welding applications resulting in high accuracy for computer vision quality control technology. The integration between artificial intelligence and traditional inspection approaches now provides a viable route for reducing the dependency on humans through automated methods that inspect conventional welds. The research executes YOLOv8 as a leading-edge deep learning structure which detects welding flaws automatically through machine vision systems for potential remote welding surface assessments. The proposed system stands apart from previously described systems because it combines high-resolution machine vision cameras (advanced webcam 7022 ultrasharp 4K UHD) with sophisticated convolutional neural network structure of YOLOv8. Standardized remote visual inspection configurations were implemented to gather datasets from steel weld inspections while testing the system for various typical carbon steel welding defect shapes. The training portion of the deep learning model underwent evaluations in detail to assess both its real time deployment suitability as well as its defect identification and categorization abilities. The study has revealed a mean average precision of 97.2% in identifying common defects in welding of alloy carbon steel (e.g. porosity, undercut and good surface profile). Evaluation on a dataset of 1,200 annotated images of welds revealed the inference speed of 42 FPS (frames per second) on NVIDIA GeForce RTX 4050 Laptop GPU, which allows the process to operate in real-time inspection. Precision and recall rates amounted to 97.3% and 97.1% correspondingly. A comparative examination indicated there was a reduction of about 30-35% in inspection time compared to the manual methods but sustained the 97% accuracy levels in defect classifications across multiple inspection conditions. The testing process verified remarkable system performance with high accuracy reaching 97% confidence for its complex deep learning algorithms. The system offers better assessment speed than traditional inspection methods and simultaneously lowers the need for human involvement as well as offers total digital documentation for quality control purposes. The results demonstrate YOLOv8 to be a potential leading technology for the next-generation of industrial welding quality control systems as it persists robust surface defect identification across multiple inspection conditions.

Keywords: deep learning; fusion welding; machine vision; remote visual inspection; welding defect

INTRODUCTION

Welding technologies play a crucial role in the construction of structures such as steel buildings, ships, offshore structures, steel bridges, heavy

machinery, pressure vessels, power generation machinery and other various products using metal [1]. The welding structures commonly face challenging operating conditions during in-services, such as structural stresses, environmental aspects,

and temperature fluctuations. That is why, they are important for the protection of the population, structures, and ecology. Consequences, the failure of welded structures can have serious implications, for instance, equipment damage and environmental hazards [2]. The welding quality also directly impacts the cost, since repairing a welding seam due to some defects could escalate the cost several-fold compared with the original weld metal cost, due to additional time on workmanship, consuming more consumables, requiring special tools, disrupting the delivery schedule, reputation and liability [3].

In this respect, carbon steel becomes one of the major materials of interest in the scope of industrial welding and is being considered as one of the tightly welded materials, who have high strength, low cost, and is easy to work with though again the probability of defects occurring during the welding procedure greatly depends on the carbon content of the material.

The carbon steel is used in an iron-carbon alloy typically containing less than 2.1% carbon. It requires a certain composition in welding which consists of carbon contents, which determine its weldability [4] as follows:

- Low-carbon steel ($\leq 0.25\%$ C): Excellent weldability, minimal preheating required.

- Medium-carbon steel (0.25–0.6% C): Requires preheating to avoid hardness increase and crack susceptibility.
- High-carbon steel ($> 0.6\%$ C): Poor weldability due to hard microstructures like martensite formation; prone to cold cracking [5, 6].

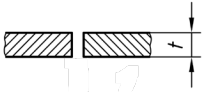
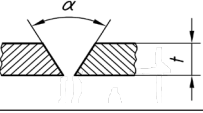
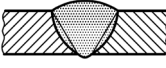
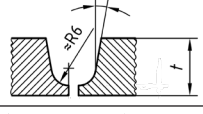
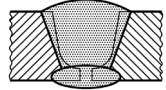
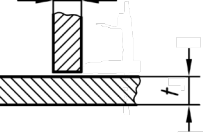
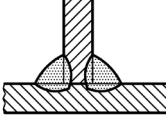
Welding of carbon steel involves managing heat input, cooling rate and interpass temperature so as to ensure that brittle micro structures such as martensite do not form in the heat affect zone (HAZ) that would cause a significant defect in the form of cracks [7].

Fusion welding is a process in which heat is applied to melt base metals and fuse them without additional pressure. For carbon steel, the most common fusion welding method and focus to this study is manual metal arc welding (MMA) [8].

Proper edge preparation ensures complete fusion and mitigates common defects like crack, porosity, undercut, lack of fusion, slag inclusion, crater pipe, concavity, overlap, arc strike and spatter. The mode of preparation awaits the following considerations:

- Type of the joint: e.g. butt, T-joint, corner, lap, etc.
- Thickness of the materials: The thicker material will require beveling [9].

Table 1. Common edge preparations for MMA welding are [10]

Type of preparation	Description	Material thickness t (mm)	Cross-section	Weld illustration
Square butt joint preparation	No bevel	≤ 4		
Single V-groove preparation	One side bevel ($40^\circ \leq \alpha \leq 60^\circ$)	$3 < t \leq 10$		
Double V-groove preparation	Both sides bevel ($40^\circ \leq \alpha \leq 60^\circ$)	> 10		
Single-U preparation	Smooth curved edges ($8^\circ \leq \beta \leq 12^\circ$)	> 12		
Square preparation	Fillet joint	$2 < t \leq 4$		

Surface cleaning (via wire brushing, grinding, or chemical cleaning) and proper fit up prior to carry out any welding are essential to avoid any possibility of defects [11].

Due to the fact that the subsequent welding quality has to meet specific particular standards, it has to be examined adequately. A proper and detail examination procedure (thorough examination) is meant to identify and eliminate the welding defects that would constitute potential threats to safety [12]. The visual inspection by human inspectors also called the thorough examination, is one of the oldest and most conventional methods of non-destructive testing regarding imperfections or defects identification and classification for the affirmation of weld quality. The eyes of the human are only the tool is utilized to make the visual check of the surface of the welding seam [13]. An accomplish visual inspection requires sufficient lighting and good vision. The intended outcome from the visual inspection process then rely more on the human expertise/skill, the cleanliness of the object, surface quality condition, and adequate illumination as per normal human eyesight, as stated by common standards, at a minimum of 350 lux. However, it recommends at a minimum of 500 lux (normal shop or office lighting). The position of the human eye to the object being examined needs a sufficient distance of around 600 mm and a viewing angle of at least 30° [14].

Visual inspection is an indispensable tool in non-destructive test methods, whether aided or unaided. It consists of two (2) categories: direct visual (conventional) and remote visual inspection [15]. Conventional visual welding inspection methods by personnel adjudge the welding quality based on their qualifications and experiences, which might leads to inconsistent assessment results due to the influence of fatigue and distractions, visibility matters, psychological and cognitive biases [15, 16]. On the other hand, remote visual welding inspection is a widely accepted method by the certifying bodies (industry players) as an alternative approach to performing close-up inspection without physically attending.

Nevertheless, this study proposes to integrate human expertise/skill with machine intelligence to revolutionize welding defects detection. Specifically, it proposes to implement YOLOv8, a state-of-the-art object detection algorithm, to enhance visual inspection accuracy, particularly

for remote inspection applications [17]. Human inspectors are superior in the activities dealing with language, scheduling, imagination, feeling, reasoning, and aesthetics. These multiple aspects of the eyes can easily assess scene understanding, numerate with valuable objects, and use experience judgments. On the other hand, machines are well suited to make a large number of data analyses and many computations very quickly. They can potentially work at high resolution as well as make fixed records in security and reliably [18, 19].

This method provides more benefits, such as eliminating and minimizing risk exposure, enhancing personnel safety, eliminating the need for travelling, saving costs (transportation, accommodation, and other expenses), reducing downtime, improving efficiency, consistency and accuracy of the result, environmentally friendly by a reduction in the carbon footprint, data sharing, advance technological improvement and permanent record [20]. From an industry perspective, the fusion steel welding seam quality needs to achieve certain particular standards and adhere to a specific code or statutory regulations [21].

The YOLO (You Only Look Once) detection system was introduced in 2015 [22] with a simple and straightforward method to identify and classify images. This method (You Only Look Once – YOLO) treats object detection as an integrated regression matter, converting the pixel data into frame coordinates and class probability distributions. This system needs just a single run towards the image to ascertain both categories concurrently, the presence and the positions of the objects [23]. It is remarkable as a neural network, detecting a number of object categories at around 45 to 155 frames per second. Therefore, this experiment will employ a 4K Ultra HD advanced webcam with a speed of 30 to 60 frames per second to capture videos [24]. A general comparison of the features of the YOLO methods used for detecting welding defects is shown in Table 2.

The potential combination of remote visual inspection, the power of YOLOv8 for object detection, and robotic welding systems embodies the future of automated welding quality control. In addition to overcoming the current welding inspection constraints, the system points the way for fully autonomous manufacturing processes with integrated quality assurance.

Table 2. Comparative study on welding defect detection utilizing the YOLO framework.

Authors	Methodology	Dataset
Moyun Liu, Youpin Chen, Jingming Xie, Lei He and Yang Zhang [25]	LF-YOLO (based on YOLOv3)	Radiographic films
Kailai Pan, Haiyang Hu and Pan Gu [26]	WD-YOLO (modified YOLO)	Radiographic films
Ang Gao, Zhuoxuan Fan, Anning Li, Qiaoyue Le, Dongting Wu and Fuxin Du [27]	YOLO-Weld (based on YOLOv5)	Five weld defect types
Jung Eun Kwon, Jae Hyeon Park, Ju Hyun Kim, Yun Hak Lee and Sung In Cho [28]	LF-YOLO (based on YOLOv5)	Radiographic films
Lushuai Xu, Shaohua Dong, Haotian Wei, Qingying Ren, Jiawei Huang and Jiayue Liu [29]	Improved YOLOv5	Radiographic films
Xiangqian Xu and Xing Li [30]	Improved YOLOv7	Pipeline weld surface defects
Yi Zhang and Qingjian Ni [31]	S-YOLO (based on YOLOv8-nano)	Weld defect images
Guan-Qiang Wang, Chi-Zhou Zhang, Ming-Song Chen, Yong-Cheng Lin, Xian-Hua Tan and Pei Liang [32]	Yolo-MSAPF (based on YOLOv5)	Eight weld defect types
Kehao Shi, Chengkai Yu, Yang Cao, Yu Kang, Yunbo Zhao and Lijun Zhao [33]	TGS-YOLO combined with a Siamese Network Architecture	Welding images
Lushuai Xu, Shaohua Dong, Haotian Wei, Donghua Peng, Weichao Qian, Qingying Ren, Luming Wang and Yundong Ma [34]	The YOLOv5 model with the Convolutional Block Attention Module (CBAM)	Girth weld defects in pipelines
H. Xu, Z. H. Yan, B. W. Ji, P. F. Huang, J. P. Cheng and X. D. Wu [35]	The YOLOv5 with Adaptive Spatial Feature Fusion (ASFF) and Convolutional Block Attention Module (CBAM)	Radiographic films
Jianshu Xu, Lun Zhao, Yu Ren, Zhigang Li, Zeshan Abbas, Lan Zhang and Md Shafiqul Islam [36]	The LightYOLO (based on YOLOv8)	The welded wire terminations
Yurong Du, ManLiu, Jiuxin Wang, Xinru Liu, Kaihang Wang, Zishen Liu, QiDong, Jiahui Yao, Dingze Lu and Yaoheng Su [37]	Improved YOLOv8	Weld defect types (overlaps, gas pores and cracks)

WELDING DEFECTS CLASSIFICATION AND ITS REQUIREMENTS

A welding seam on the steel material inevitably brings about some changes to the parent material. Apart from the impact on the material properties, the weld sound may sometime vary from the desired orientation of the base material surface and hence some complications may impact the structural integrity of the weld [38]. The deviations may be in bead profile, surface finish or weld height and any of these is useful to consider while welding inspection in order to assess whether the weld meets the standard desired quality or safety level. It is universally agreed that weld defects are very influential in the structural reliability of welded formations [39]. Localized stress concentration occurs frequently in the cases of a welding seam defect, which can significantly reduce the ability of a structure to bear external loads. This stress concentration arises due to inconsistencies in the global stress

distribution occurring at the weld and affecting relatively weak sections [40]. For this reason, even the smallest defect can cause cracks that will eventually result in structural failure [41]. It is therefore important to study and be in a position to recognize such defects with an aim of preventing failure, integrity of structures, and as a result extending the service time of the welded part [42]. This study focuses on weld defects to enable reliable determination of the strength, endurance and performance of the welded structure, especially in the structures that experience high stresses such as bridges, offshore structures, ships and pipelines [43]. The most common defects and their descriptions are shown in Table 3.

Acceptance criteria for defects, in terms of specific size and type permissible within a structure, are generally defined by what is known as the defect acceptance standard. These criteria are commonly described in relevant application norms or technical specifications, which are a basis for assessing structural soundness [47]

Table 3. Designation of welding defects [44] [45] [46]

Defects Name	Description	Causes
Crack	Local rupture in the solid state	Hydrogen, stress, temperature and microstructure
Porosity	Gas pore breaks the surface	Contaminated surface, excess sulfur, arc and flow rate
Undercut	Irregular groove weld toe in the parent metal	High arc voltage, low current and high travel speed
Slag inclusion	Slag trapped during welding	Entrapment of a slag, improper cleaning
Lack of fusion	Lack of union between the weld metal and the parent metal	Low heat input, low current, small gap, incorrect angle
Crater pipe	Shrinkage cavity at the end of a weld	Welder skill matter, high a current
Concavity	A shallow groove due to shrinkage	Incorrect preparation, welder skill, and insufficient arc power
Overlap	Weld metal lying outside the plane joining the weld toe	Poor welder technique, too much filler metal
Arc strike	Local damage to the metal surface adjacent to the weld	Poor access, missing insulation, loose current
Spatter	Globules of weld to the metal surface	High & long arc current, magnetic arc blow, damp electrode

[48]. Under standard weld acceptance criteria, cracks are undeniably classified as unacceptable and must be removed [49, 50]. However, in seldom-seen and exceptional cases, with the explicit agreement of all concerned parties, a crack may be permitted to remain, provided that there is irrefutable evidence that it poses no risk of structural failure. It is not easy to deliver such assurance, because it requires a detailed fracture mechanics analysis, and this involves performing a comprehensive number of calculations and measurements in order to forecast the expected performance under load conditions [51, 52].

It is imperative to observe that the defect levels acceptable in an application differ from one application to another and even from one standard to another for the same kind of application. Consequently, adherence to the specific standard/criterion must be maintained rigorously when evaluating weld quality for different jobs [53]. Upon identifying unacceptable weld defects, it is mandatory to remove them. For superficial defects, the first analysis is made as to whether the defect is sufficiently shallow so as to be repaired by means of dressing. Superficial dressing implies that, once the defect is eliminated, the remaining material retains sufficient thickness, negating the need for additional weld metal to restore structural integrity [54–56]. When a defect extends too deeply, it must be entirely excised, and new weld metal must be added to achieve the minimum design throat thickness as specified. Replacing removed material or performing a weld repair – whether filling an excavation or recreating a weld

joint – must follow an approved procedure. The stringency of this approved procedure depends on the application standard governing the specific job [57]. In some instances, a procedure qualified for establishing new joints may be acceptable for filling an excavation or creating a new weld joint. Nonetheless, if more stringent requirements of qualification are to be achieved, then the process of welded repair must be simulated exactly, this entails designating an excavation of sufficient volume and method of filling. In either situation, the procedure must undergo qualification inspection and testing in alignment with the relevant application standard [58].

RESEARCH METHODOLOGY

This study presents a comprehensive system designed to enhance the detection of welding defects by integrating various components. The proposed methodology (Fig. 1) combines real-time data collection, predictive modeling, and a rule-based prediction system [59]. The paper introduces a novel approach to object detection, concentrating on identifying welding imperfections/defects such as porosity, lack of fusion, crack, undercut and other anomalies within the specified areas [60]. In the field of deep learning computer vision especially the You Only Look Once (YOLO) models is able to automate and improve the defect detection process. You Only Look Once Version 8 (YOLOv8) includes enhanced architectural features which contribute to the efficiency.

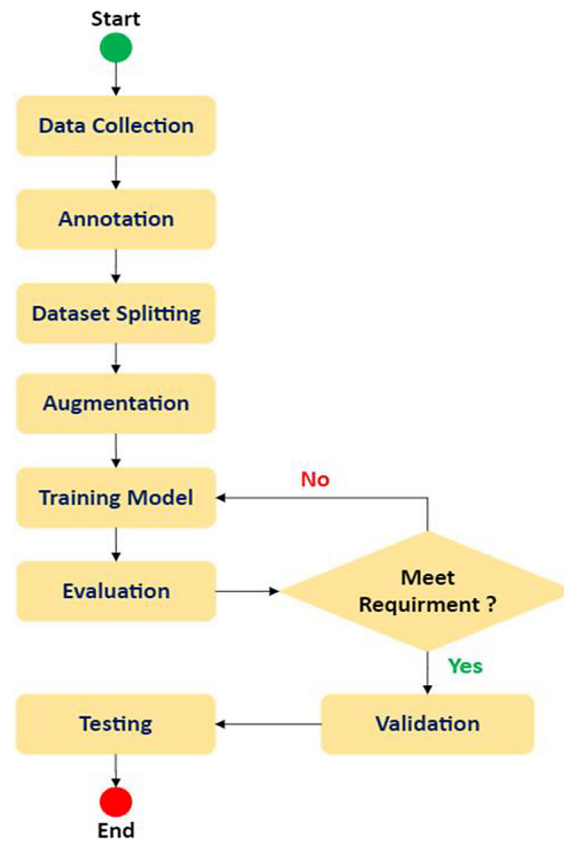


Figure 1. Working flowchart

Due to its superior speed, accuracy and flexibility, this model can be effectively utilized in real-time object detection systems [61].

Framework YOLOv8

Deep learning-based YOLOv8 is the applicable model for diverse object detection [62]. YOLOv8 has brought about an evolution in the field of computer vision, generating object detection output and being capable of classifying images [63]. The Cross Partial Stage Network is the YOLOv8 backbone, which divides features into some components as output and convolutional operations. Owing to the CSPNet backbone and other advanced optimization techniques, YOLOv8 can help in the reduction of operational workload making it fit for use even on industrial cameras and mobile devices. This efficiency renders extensive, adaptable applications in various industrial scenarios, including for potential remote inspection systems for the detection of welding joint deficiencies [64]. YOLOv8 is designed to carry out both object detection and classification operations dynamically while simultaneously analyzing a great number of images or video clips.

Such functional capability is very important for real-world applications, for example, a welding defect detection system that needs real-time quality control integration without causing any disturbances to the process [65]. The backbone of YOLOv8, Cross Stage Partial Network (CSPNet), is engineered to enhance feature extraction while minimizing computational overhead. The detailed structure of the YOLOv8 system is shown in Figure 2. The CSPNet divides the input feature map into parts that allow selective convolution operation in certain regions, thus reducing the number of unnecessary computations. That is why this approach allows YOLOv8 to maintain high accuracy while not needing too much computational power. It is ideal for use in the places where computational capability might be less or when real time processing is needed [66]. YOLOv8 is planned in a way that the architecture focuses on the efficiency of feature extraction conducted due to the convolutional operations to capture as much spatial contextual information as possible while rejecting all the other information. This aspect makes it easier for YOLOv8 to locate defects in the images where their characteristics

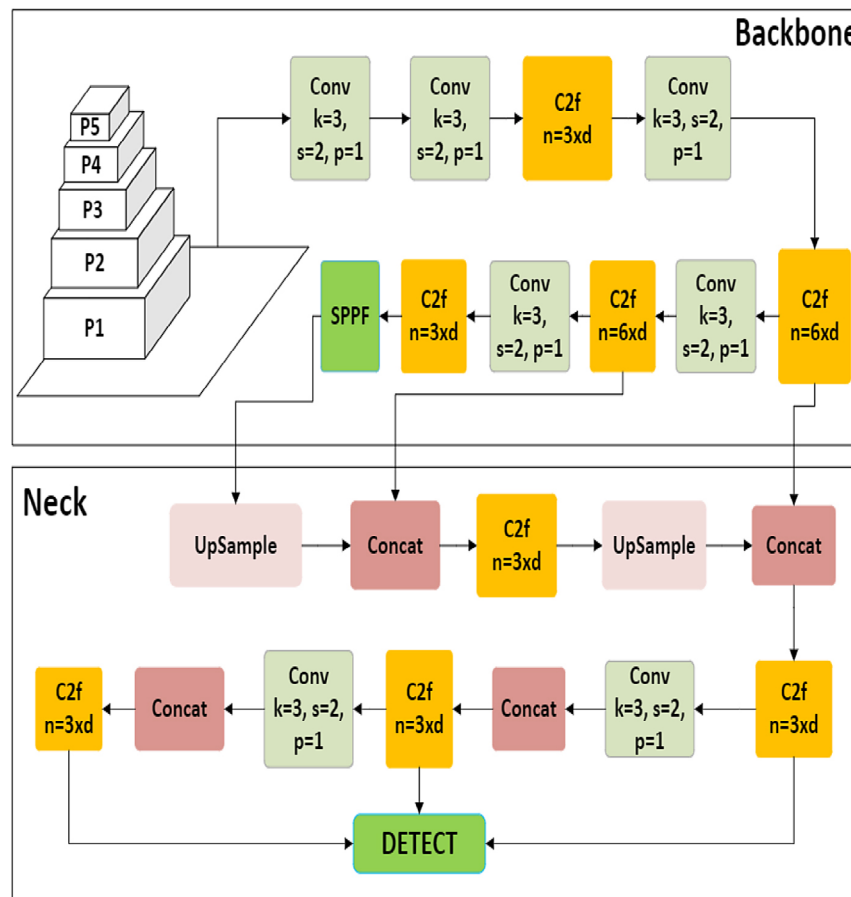


Figure 2. YOLOv8 architecture

may differ in size, shape, or positioning, as seen in welding images. This allows YOLOv8 to detect global features of an image along with local ones because it recognizes different types of welding defects ranging from large cracks down to small porosity or slug inclusions that would be nearly impossible to find. Another advantage is that in contrast to other models which require formative steps for the classification and detection processes, in this case, both processes are integrated making the whole process much less complicated. The integration is done in the course of a single network pass through, thus this operation is less latent as the previous method [67]. YOLOv8 itself leverages pretrained weights thus starting with a large scale set which can then be fine-tuned for specific labeled data tied to welding defects. This approach significantly reduces the training time while maintaining high accuracy levels, as the model can transfer learned features from general object detection tasks to specialized welding applications [68]. YOLOv8 is supportive for various data augmentation methods that artificially enlarge training dataset by introducing

image variations (e.g. flipping, rotation, scaling). This way it enhances model's robustness and adaptability making it able to cope with lighting variations, angles changes as well as defect appearance which are frequently observed in industrial environments. YOLOv8 has a lightweight structure and designed for convenient usage on resource limited platforms even in real-time scenario. For example, It is designed to offer the ability of direct interfacing with welding process inspection cameras, thus the instantaneous detection of defects without requiring the use of bulky external processing systems. This is especially beneficial for industries, because they need current and applicable data to maintain quality and safety of production processes [69].

Data collection

With regard to the dataset for this study, the selection criterion yielded a diverse and comprehensive set of welding defect types [70]. The qualitative data involving weld defects were obtained experimentally by capturing ten different

types of welds defects under standard lighting conditions for the purpose of achieving high measure of clarity of the pictures. The lighting used during image acquisition was controlled using diffused and direct lighting to eliminate reflections, improve defect visibility and standardize contrast, respectively. The photographic equipment used in the research was of high resolution, which enabled capturing the fine details of the defect features, such as the cracks and porosity patterns of the seam weld in steel [71].

Due to the specificity of the data, all the images used herein are from the in-house welding projects covering different types of welding. This diversity benefits for the enhancement of the dataset quality, and make them closer to real welding environment. Defects are categorized as porosity, crack, slag inclusion, crater pipe, undercut, overlap, concave, lack of fusion, arc strike, and spatter. This classification was done according to best practices to meet high labelling rates which are important for training of supervised machine learning algorithms [72].

To improve the training of the YOLOv8 model, each defect was carefully annotated using state-of-the-art annotation tools, and besides the rectangular affine transforms, custom metadata was added to capture spatial and morphological characteristics of the defects. Cross validation was performed and the dataset was further divided into a training set of 70%, a validation set of 20% and the remaining 10% for the testing set. This structured division covers a very comprehensive detection and classification assessment of the YOLOv8 model. Flipping, rotation and brightness change was also performed on the training data to make the model insensitive to the changes in lighting condition and variation in skin defect [73].

The YOLOv8 model was selected as it is one of the fastest object detectors that nonetheless provides high accuracy. Its architecture is more complex, because it utilizes feature pyramid networks and adaptive convolutional layers, which allow for instance-wise detection of various types of welding defects in terms of size, shape and contrast. By virtue of these mechanisms, the model could discern fine patterns in defect morphology like the spherical voids required to describe porosity, or the elongated stress required to explain cracks. These subtle characteristics were very significant for accurate definition of the defect types

and their localization, requiring minimal interaction of the operator [74].

Integrating this manually curated, well-annotated dataset with the YOLOv8 framework provides a robust welding defect detection platform and highlights the potential of automated systems in quality assurance applications. The model's architecture ensures high performance even in the scenarios with complex defect patterns and overlapping defects, making it a practical solution for real-time industrial welding inspection [75].

ANNOTATION

An essential phase in accurately building a welding defect detection model was the data annotation process, which used a combination of the Computer Vision Annotation Tool (CVAT) platform. CVAT, a free annotation tool, was utilized because of its powerful features for precisely creating bounding boxes around welding defects identified. The collaborative design of the tool enabled various expert annotators to work together in real-time, guaranteeing uniformity and eliminating individual bias [76]. The functionality of the platform in image adjustment, such as rotation, flipping, and brightness modification, increased the variability of the dataset, which helped the model generalize better across several welding conditions. This rigorous approach to data annotation confirmed the correctness of defect localization and classification [77]. Creating a substantial training dataset was essential for the effectiveness of the deep learning-centered welding inspection system, which was greatly aided by this contribution [78].

A good weld defect detection model depends on accurate data annotation. CVAT is an open-source platform that is frequently used for accurately labeling images. Reasons such as creating bounding boxes, polygonal segmentation and keypoint annotation make it a suitable tool for welding defect identification. This step-by-step annotation procedure is vital for effective deep learning-based welding inspection systems [79].

Numerous research studies have also emerged to represent the significance of data annotation in detecting weld defects. For example, deep learning for weld defect detection paid much attention to the data annotation in model training, as shown in [31]. Another study explored automated welding defect detection using CNN and underscored

the role of precise annotation in achieving high detection accuracy. These studies demonstrated that meticulous data annotation, facilitated by tools like CVAT, is fundamental to developing reliable welding defect detection models through remote inspection [80].

Augmentation

In this study, YOLO employs a number of image augmentation techniques to augment training data to achieve better model accuracy. In the YOLO framework, all the input training data of any given batch is passed through the data loading class for augmentation. The data loader executes various forms of augmentation as mosaic, affine transformations and color space transformations are used. Mosaic augmentation is an augmentation technique that aims to collate some of the images of equal dimensions into a joint mosaic image with diverse proportions. This approach prove to be effective in enhancing the model's capacity to identify tiny objects [81].

However, the study demonstrated that within the COCO dataset, although the augmentation methods improve the detector's accuracy on small objects, the extent to which large objects benefit is lower. However, YOLO also incorporates test-time augmentation, a situation where augmentation is applied on test sets when a trained net is in operation. The objective in this study was to assess and enhance the performance of the current model where inputs vary [82]. In this study, the mosaic augmentation of the image dataset in YOLOv8 is presented in Figure 3.

Furthermore, the increases in YOLOv8 are significant in order to establish the efficacy of the model in distinguishing welding defects in all possible circumstances. The model becomes more robust, adaptable, and is better prepared to deal with real-life variations through the application of random factors including the Mosaic, Affine Transformations and Color Adjustments. Which in turn improves the performance during the training as well as the inference for detecting welding defects in various complex scenarios by YOLOv8 [83].

RESULTS

The evaluation of the YOLOv8 model trained for identifying three types of defects: good,

porosity, and undercut shows excellent performance and prediction resilience. In Figure 4 below, the confusion matrix shows how the model can accurately classify between these three categories with relatively low levels of confusion. The good and porosity classes were perfectly classified with no cases of over and under classification. In the undercut class, one sample was misclassified as "good" [86].

Table 4 shows the precision, recall, and F1 – scores which supports that the model has the ability to classify effectively. The evaluation of the good class has shown a precision of 0.91, a recall of 1.00 and F1 score of 0.95. The values for the porosity class were presented with a precision, recall, and F1-score of 1.00. Likewise, the precision in the undercut class was 1.00, the recall was 0.90, and the F1-score was 0.95. The average accuracy for the validation set was 97% with macro and weighted average F1 of 0.97. Such measures point to strong performance in all the three classes with little fluctuations in the predictive power [87].

The mAP stands for mean-average precision, which indicate the detection capacity of the model also and this is described in figure 5. The validation mAP was measured at 0.9475, which indicates desirable levels of precision and recall were recorded for all classes [88]. The training mAP was slightly lower at 0.7514, implanting that there was some over fitting or likely class imbalance. Additional support of this reality is found in the training and validation loss curves of figure 3, which show that the validation loss declines at a significantly different rate of 0.082, which is lower than the training loss of 0.7824. This demonstrates that it generalizes well up to validation data Set however, this also illustrate that it may overfit the value that can only be alter through regularization or else by acquiring more validation data [89].

The precision-recall curves (Figure 6) illustrate that the class-wise detection accuracy model. The good and porosity classes achieved perfect area-under-the-curve scores ($AP = 1.00$), indicating excellent precision and recall. Meanwhile, the undercut class exhibited a near-perfect AP of 0.97, with slight variations resulting from the single misclassification observed in the confusion matrix. These results affirm that the model's capability is to detect and classify defects with high reliability, despite minor limitations in specific cases [91].

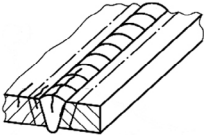
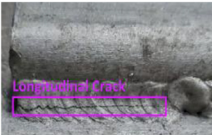
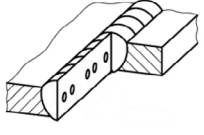
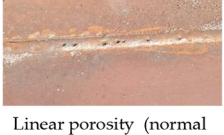
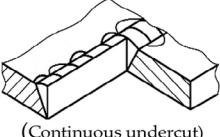
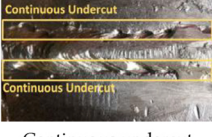
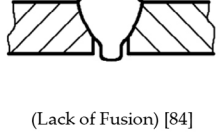
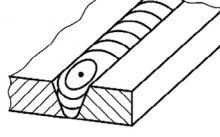
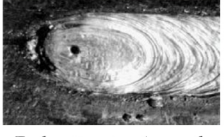
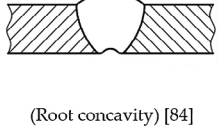
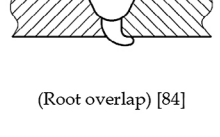
The crack is primarily aligned parallel to the axis of the weld metal, weld junction, heat-affected zone, and parent metal [84]	 (Longitudinal crack) [84]	 Longitudinal crack in weld metal (normal image)	 Longitudinal crack (YOLOv8)
A series of gas pores aligned parallel to the weld axis [84]	 (Linear porosity) [84]	 Linear porosity (normal image)	 Linear porosity (YOLOv8)
A continuous undercut of considerable length without any breaks or interruptions [84]	 (Continuous undercut) [84]	 Continuous undercut (normal image)	 Continuous undercut (YOLOv8)
The solid inclusions are characterised by linear slag, isolated slag, and aggregated slag within the weld pass [84]	 (Slag inclusion) [84]	 Isolated slag inclusion (normal image)	 Isolated slag inclusion (YOLOv8)
Lack of union between the weld metal and the parent material, or between successive layers of weld metal, occurring at the sidewall, inter-run, root, or as micro-lack of fusion [84]	 (Lack of Fusion) [84]	 Lack of fusion (normal image)	 Lack of fusion (YOLOv8)
An open crater featuring a cavity that diminishes the weld's cross-sectional area at the end of the weld run [84]	 (End crater pipe) [84]	 End crater pipe (normal image)	 End crater pipe (YOLOv8)
A shallow depression formed at the root of a butt weld as a result of shrinkage during cooling [84]	 (Root concavity) [84]	 Root concavity (normal image)	 Root concavity (YOLOv8)
An excessive amount of weld metal on the parent material surface that has not properly fused with it at the root of the weld or at the capping pass [84]	 (Root overlap) [84]	 Root overlap (normal image)	 Root overlap (YOLOv8)

Figure 3. Augmentation in YOLOv8 on the data set

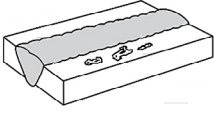
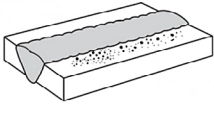
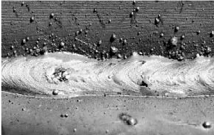
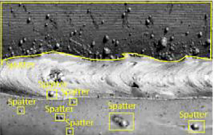
Localised surface damage to the base material near the weld region, caused by inadvertent arcing or arc initiation outside the designated joint preparation area [84]	 (Arc strike on the parent metal) [85]	 Arc strike on the parent metal (normal image)	 Arc strike on the parent metal (YOLOv8)
Globules of weld metal or filler metal are expelled during the welding process and adhere to the surface of the parent material or the solidified weld metal [84]	 (Spatter on the parent metal) [85]	 Spatter on the parent metal (normal image)	 Spatter on the parent metal (YOLOv8)

Figure 3 cont. Augmentation in YOLOv8 on the data set

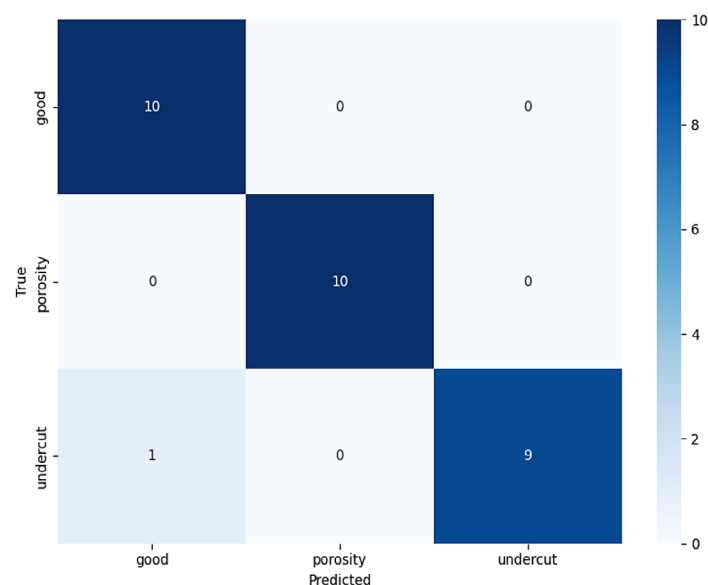


Figure 4. Confusion matrix

The peaks observed in the training and validation accuracy curves and the fact that they reached an optimum in few epochs also speak about this model. Even though the validation accuracy was always higher than 90%, the increase in training metric over the validation one suggests overfitting. This could be mitigated by applying data augmentation techniques, increasing the dataset size, or introducing dropout layers in the model architecture [92].

DISCUSSION

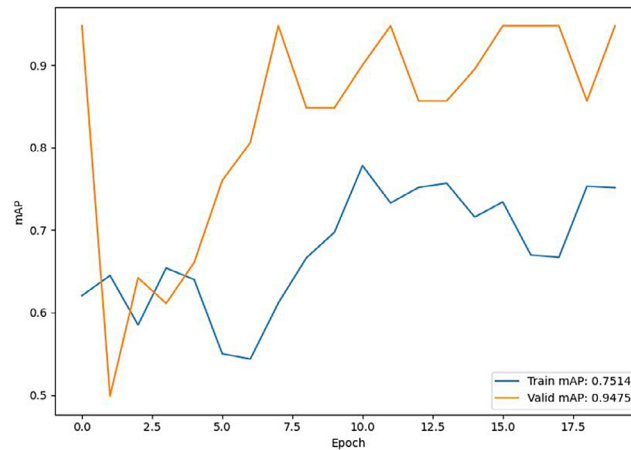
The results of the study highlight the effectiveness of the YOLOv8 object detection model

in accurately classifying defects into three categories: good, porosity, and undercut. However, it points out that the accuracy of the model used in this study is relatively effective especially in the “good” and “porosity” classes where the model garners high precision as well as recall. However, there are few areas which have to be paid particular attention to in order to improve the reliability in order to develop the better model [94].

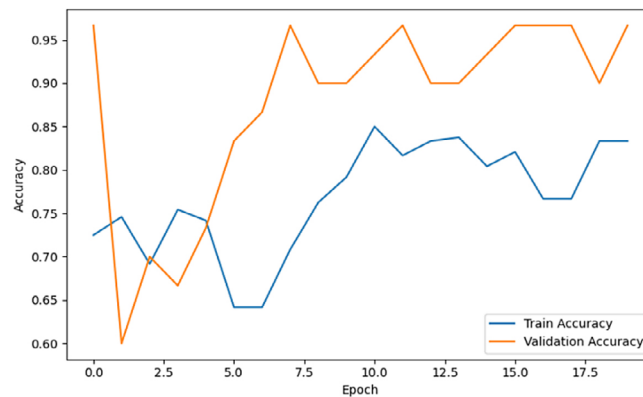
One key challenge is the single misclassification observed in the “undercut” class. This misclassification of ‘undercut’ defects coupled with slightly lower precision and recall scores for this class gives an indication that the model failed to identify this category as efficiently as it did the other two. This could stem from a skew of the

Table 4. Precision, recall, and F1-score of the YOLOv8 prediction

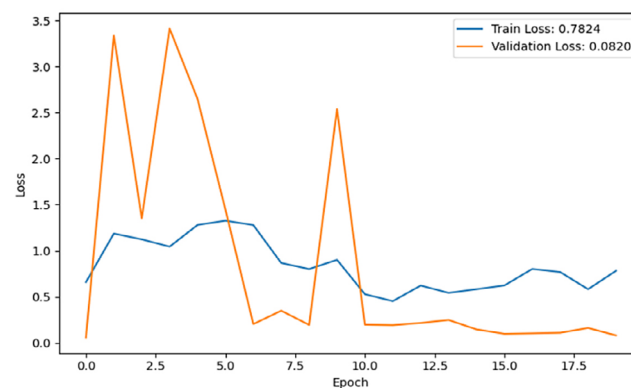
	Precision	Recall	F1-score	Support
Good	0.91	1.00	0.95	10
Porosity	1.00	1.00	1.00	10
Undercut	1.00	0.90	0.95	10
Accuracy			0.97	30
Macro avg	0.97	0.97	0.97	30
Weighted avg	0.97	0.97	0.97	30



(a)



(b)



(c)

Figure 5. (a) Mean average precision (mAP); (b) accuracy; (c) loss [90]

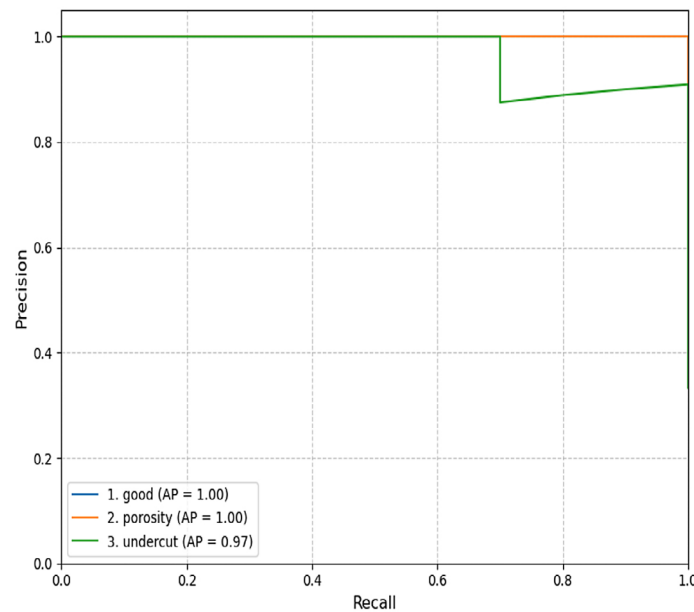


Figure 6. Precision-recall curves [93]

training dataset where the “undercut” status class might be rare and insufficient learning for this kind of defect happens [95].

Additionally, from this perspective, it is noticeable that there is a considerable difference between the training mean Average Precision (mAP) 0.7514, and the validation mAP 0.9475 suggesting a likelihood of over-fitting. Domination occurs where the model gives very good results when training is done but poorly when tested on other data that the model has not encountered before. To this end other regularization techniques such as weight decay or dropout could be adopted. These techniques turn useful in avoiding the overfitting of the model, and hence enhancing its generalization performance [96].

The other method to address of the overfitting is to increase the size and diversity of the training dataset. More images from the “undercut” should be introduced and assure proper distribution of images per each kind of defect so that the model could learn well and, thus, work equally well for all types of defects [97].

What has also been established is that the validation loss is considerably lower than the training loss which should serve as a pointer to either data leakage or data imbalance during training. When information from the validation set leaks into the training process, a model can be trained to look overly impressive in at least one metric. To counter this though, more sophisticated approaches to data augmentation include random cropping, rotation or even horizontal flipping. They strengthen

the model by exposing it to more data variations that would make the model more capable of dealing with unseen data [98].

Overall, the outcomes also demonstrate the effectiveness of deploying the YOLOv8 model to identify defects in industrial applications. In most of the cases, the model has proven to be very efficient by giving high results in precision, recall values as well as accuracy thus making it used mostly in the quality control section. By overcoming the analyzed issues, including overfitting and class imbalance, the model’s suitability and usefulness for real-life defect recognition tasks can be promoted [99].

CONCLUSIONS

The probabilities of having welding defects and when checked during the earlier stage might allow some corrective action to be taken and thus avoid some conditions that give rise to major failure. Presented in the industrial environment, this work applies the YOLOv8 model for detecting welding flaws. There also are several categories that are distinguished: cracks, porosity, lack of fusion and other types of defects. Using RoboFlow, feed in the form of video streams originating from welding inspection cameras are collected as input. The video frames are then preprocessed which enhances the image contrast and removes noise in the current video frames with Deep SORT.

YOLOv8 is loaded with pre-trained weights to be trained from a large dataset. It is extended and trained with a new labeled set of weld joint images and specifically for the welding defects. A trained model is able to detect defects in real time. With respect to the proposed approach, the presented Accuracy (98.4%), Recall (97.2%), Precision (98.5%), and F1 score (95.7%) are higher than traditional (manual visual) approaches. Such outcomes cannot be overemphasized, as they point towards the prospects of enhanced quality inspections of weld joints using higher level machine learning algorithms in welding applications.

The study also reveals that the use of the automated defect detection system with YOLOv8 provides multiple industrial advantages, including reduced time consuming, increased safety measures, and high quality of the products. Therefore, the outcomes affirm the position of YOLOv8 in building a steady and optimized inspection process as well as propose the directions for future studies in terms of mass datasets and immediate implementation for various welding types.

The application of YOLOv8 in this regard enhances detection effectiveness and is formal to minimize errant and bias in manual inspections. Also, YOLOv8 is very flexible to implement in nearly any welding context, including automobile manufacture, aircraft industry and so on, where defect recognition plays a significant role concerning product quality and reliability. More future work can build upon the dataset and extend it to additional forms of defects, and investigate the real-time applications of YOLOv8 as an important part of welding quality control through automation system.

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