AI-based Detection of Pressure Vessel Internal Damage Mechanisms

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***Abstract* — Preserving the human factor while mitigating risks associated with confined spaces, cutting down on the overall time of the inspection process, and optimizing regular equipment maintenance costs are the three most important factors for the success of the inspection process in oil and gas fields. Due to cost concerns and to ensure safety, the pressure vessel inspection process requires alternatives to traditional labor-intensive visual inspection techniques. This paper proposes a deep learning (DL) model as an intelligent and accurate tool for visual inspection of pressure vessels using a training dataset of 5000 real internal shell surface on-site images from the Abu Madi gas field of the PETROBEL Company, Egypt. A six-year-experienced Non-Destructive Testing (NDT) inspector was leveraged for manual labeling of the dataset. The present detection model utilizes You Only Look Once (YOLO) v8 model from v5, v8 and v10 models to diagnose whether the pressure vessel's inner surfaces of shell is in good condition or includes damage. The developed YOLO v8 multi-class identification model successfully detects the state of the pressure vessel's inner shell; good condition, or in the existence of damage, corrosion, pitting corrosion, mechanical damage, or brittle fracture. After training the model on the used on-site dataset images, the test process reveals a detection accuracy up to 93.3%. During the test process, if a single image contains good and damaged parts or two different types of damage, the model can differentiate between those cases. Applying this model in the inspection process will reduce costs by excluding the need for scaffolding and qualified inspectors and reducing the number of injuries and fatalities recorded due to confined spaces.**

Keywords: pressure vessel; internal visual inspection; damage mechanisms; defect detection; YOLO v8 model.

I. Introduction

In the oil and gas industry, pressure vessels play a vital role in various operations, including storage, separation, and filtration processes, where pressure vessel considered as a container that can sustain internal or external pressure. Pressure vessels are built in compliance with American Society of Mechanical Engineers Boiler & Pressure Vessel Code (ASME BPVC). These standards usually restrict design basis to an exterior or internal design pressure of no less than (103 kPa) [1]. The safety of these vessels is crucial since the stored substances are highly flammable. Any failure of these pressure vessels might have disastrous effects on both the environment and public safety. Thus, it is essential to visually monitor these assets on a frequent basis [2]. The structure of vessels can be impacted by corrosion in many different ways [3]. General corrosion, which can develop uniformly on uncoated surfaces and appear as friable, non-protective rust. Pitting is a localized process that typically begins due to localized casing breaking, drifts by corrosive attack into deep wells of relatively small diameter, and can ultimately result in penetration into the shell at sporadic, isolated spots. Cracks when early detected helps avoid structure collapse or cracking and the resulting potentially catastrophic effects on people, the environment and the economy. These defects are indicators of the condition of the metal surface. The consequences of its failure extend beyond environmental and safety concerns, highlighting the significance of regular visual inspections to ensure operating integrity [4]. Considering Marcus Oil Explosion (2004) [5], a pressure vessel explosion at a chemical factory in Houston caused three fatalities as well as significant damage to surrounding structures because of incorrect modifications and poor welding. Moreover for Buncefield Explosion (2005) [5], over 2,000 citizens had to be evacuated after an explosion at a gasoline depot in the United Kingdom left 43 people injured. The mishandling of pressure vessels was a contributing factor in that tragedy. The explosion at Algeria's largest refinery (Skikda 2004) [5], left 23 people dead and highlighted the disastrous possibility of pressure vessel failures in the oil and gas industry. By identifying and monitoring the indications that may result in damage, the inspection process is essential to assess the state of a vessel. Proactive risk management becomes better by the information gathered from these inspections, which helps with future repair, replacement, and inspection strategy decision. Regular inspections play a vital role in identifying potential hazards early on, which is essential for preventing significant process safety incidents such as fires, exposure to dangerous matrials, and environmental damage [6]. Additionally, visual inspection is regarded as a basic and reliable inspection technique [7]. When using the traditional method, skilled human engineers usually visually check these assets that are situated in difficult or crowded areas. It is therefore becoming essential to relieve human engineers from risky, falling object, and high-pressure system explosion tasks even in the absence of appropriate safety protections [8].

This study suggests using three YOLO models, v5, v8, and v10 and Examine the performance of each model to select the most appropriate model for this type of dataset to determine whether the pressure vessel's internal shell is in good condition or includes any damage, which is classified as corrosion, pitting corrosion, mechanical damage, or brittle fracture. YOLO v8 achieves higher mean average precision (mAP) in comparison to versions like YOLO v5 and YOLO v10. YOLO v8 represents a substantial advancement in real-time object detection, focusing on efficiency and accuracy. The improvements made to it enable its use in numerous applications, especially in situations where rapid performance is essential.

II. Literature Review

The discussion of this literature included a number of vision-based damage detection techniques. **Pascual et al. [9]** demonstrated a system for detecting coating breakdown/corrosion based on a three-layer feed forward artificial neural network with a micro-aerial vehicle. **Maglietta et al. [10]** described three processing levels of an innovative intelligent system for autonomous visual assessment of containers. Their classification of sub-images as rust or non-rust was proposed using a new tool based on an ensemble of classifiers**. Liao and Lee [11]** employed an algorithm incorporating three distinct methodologies as a substitute for automatically processing photographs. Their images were grouped into subsets based on the hue percentage and coefficient of variation of grey levels. **Margarita et al. [12]** employed the use of digital photographs of metals to present an image-processing approach for the detection of rust zones. **Ivanoskii et al. [13]** used machine learning techniques to analyze images to detect steel flaws, which could significantly expedite the process of identifying faults and enhance its efficiency. **Zhitong et al. [14]** developed a metal surface corrosion identification model framework on the YOLO v5s. **Zhao et al. [15]** proposed the RDD-YOLO model, based on YOLO v5 and incorporated "Res2Net" blocks to form a DFPN in the neck to enhance the receptive field and extract features of different scales.

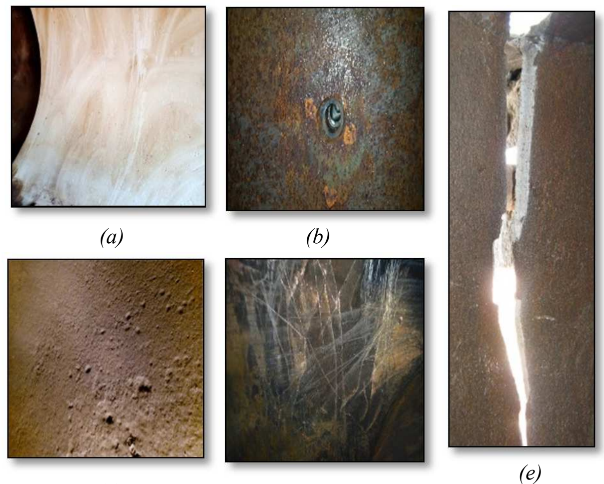
Choi and Kim [16], employed digital image processing to introduce a novel concept for analyzing corrosion surface damage rather than relying on electrochemical techniques. Their study examined corrosion events through the evaluation of morphological surface defects using digital values. **Cha et al. [17]** proposed a faster R-CNN-based structural visual examination method, allowing the quasi-real-time identification of multiple types of defects. **Atha and Jahanshahi [18]** presented various CNN-based methods for evaluating corrosion on metallic surfaces. Their findings indicated that CNNs outperform vision-based corrosion recognition methods that based on texture and color analysis using a fundamental multilayered perceptron network. **Forkan et al. [19]** created a research community working on using AI picture analysis to identify corrosion, with convolutional neural networks CNNs serving as the foundation for the innovative deep learning approach of the CorrDetector suite. **Zhang et al. [20]** proposed a surface flaw detection methodology for wind turbines utilizing portable YOLO v5s. **Bastian et al. [21]** identified corrosion in pipelines using a computer vision-based method. The pipelines proposed to be carrying gas, oil, and water. They built convolutional a uniquely neural network and used to categorize pipeline photographs based on the degree of corrosion in each one. **Jiang et al. [22]** offered a pipeline flange visual inspection method based on the YOLO v3 algorithm. To mitigate the impact of image capture scale variations on detection accuracy, the original network's multi-scale target detection was modified to incorporate five distinct scale types.

The main focus of this article is to present an approach for the immediate detection of structural defects in internal pressure vessels in oil and gas plants by emphasizing several types of visible damage. The procedure involves distinguishing internal shell surfaces that are damaged from those that are good. Thus, detecting corrosion, pitting corrosion, mechanical damage, brittle fractures, cracks, and other interior damage mechanisms affecting pressure vessels are given special attention in this work.

III. Methodology

A. Dataset Collection and Annotation

The lack of publicly available datasets is one of the major challenges in using object detection to identify internal damage in pressure vessels containing oil and gas. To overcome this limitation, this study created a new dataset specifically designed to identify different internal damage mechanisms in pressure vessels. The detection model's training dataset included 2000 real on-site images of the interior pressure vessel shell surface from PETROBEL's Abu Madi Field; 40% in good form, 35% corrosion, 20% brittle fracture, 3% mechanical damage, and 2% pitting corrosion, as shown in Fig.1.



(a) (b) (c) (d) (e)

Fig.1. (a) Good, (b) Corrosion, (c) Pitting Corrosion, (d) Mechanical Damage, (e) Brittle Fracture

Non-Destructive Testing (NDT) inspector has six years of expertise in oil and gas plant inspections annotated the dataset used in this investigation. Using the free online annotation tool Roboflow, each image in the dataset is manually labeled. A variation of image expansion methods were applied in order to increase the model's flexibility in detecting internal damages of pressure vessels and increase the dataset. These methods include saturation modification, rotation +/-90, vertical flipping, and static cropping.

To support and generalize the model's ability in real-world scenarios, several data augmentation techniques were implemented. These techniques not only enhanced the dataset by adding 3000 additional images, Table I, but they also successfully reduced the likelihood of over-fitting, which in turn increased the model's ability. The dataset was split into two groups after the augmentation process: 80% was utilized for training, and 20% was used for validation. 150 distinct photos from the original dataset (images the model had never seen before) were utilized to test the model's performance in real-world testing.

TABLE I. COMPARISON OF THE DATASET BEFORE AND AFTER AUGMENTATION.

Dataset	Original dataset	After data augmentation	Training dataset (80%)	Validation dataset (20%)
Number of Images	2000	5000	4000	1000
Good	800	2000	1600	400
Corrosion	700	1750	1400	350
Brittle Fracture	400	1000	800	200
Mechanical Damage	60	150	120	30
Pitting Corrosion	40	100	80	20

B. YOLO Architecture

Joseph Redmon et al. [23] introduced the "You Only Look Once" method for the first time in 2016. Its name comes from its unique method of identifying things and their placements by looking at a whole image only once. YOLO addresses object detection as a regression problem, compared with conventional solutions that modify classifiers for a two-stage detection process, resulting in complicated networks requiring separate training for each component. In the year 2020, Glenn Jocher introduced YOLO v5, shortly following the release of YOLO v4 [24]. Because it strikes a compromise between speed and accuracy, YOLO v5 is becoming increasingly popular. YOLO v5 includes three features. **Architecture** is the updated CSPNet backbone used by YOLO v5 to improve feature extraction while maintaining efficiency. **Performance** is suitable for real-time applications because it strikes a fair balance between speed and accuracy. Using a typical GPU, YOLO v5 can process images at around 140 frames per second. **Use cases** as it is frequently used in a range of applications, including industrial automation, autonomous driving, and surveillance

YOLO v8 improved upon YOLO v5 in several of ways, with an especially strong focus on speed and precision. It consists of three notable characteristics. **Improved Architecture** as YOLO v8 has a revamped head and backbone that improves the model's performance and capacity to recognize tiny objects. **Performance Metrics** when compared to YOLO v5, it exhibits better mAP results on benchmark datasets, especially in complex situations. **Speed** with comparable hardware configurations, YOLO v8 is intended to be quicker than YOLO v5, reaching about 200 FPS. YOLO v10 is a new real-time end-to-end object detector. Multiple evaluations reveal that YOLO v10 exceeds other cutting-edge detectors in terms of performance and latency, thus proving its superiority. YOLO v10, developed by researchers at Tsinghua University and published in May 2024 [25], represents a significant advancement in the field of real-time object detection. A crucial problem in object detection is striking a balance between computational efficiency and accuracy, which this innovative architecture attempts to solve. YOLO v10 achieves this by combining a variety of model variations, architectural changes, and creative training techniques. YOLO v10 uses a mix of training techniques and architectural advancements to address accuracy and efficiency. The fundamental idea is "Consistent Dual Assignments" in training, which removes the requirement for computationally costly non-maximum suppression (NMS) during inference and lets the model learn from rich supervision.

C. Damage Identification Model (DIM)

Detecting and accurately locating objects within image or video data is made possible by object detection, which is a crucial component of computer vision. According to Zhao et al. [26], there are two essential steps in this process: classification, which entails giving each object a unique class name, and localization, which involves demonstrating one or more things within the data that was collected. The internal damage mechanisms of pressure vessels can be identified utilizing object detection techniques. This AI-driven model can detect the many forms of damage, such as pitting corrosion, brittle fracture, mechanical damage, and corrosion, on the interior shell of the pressure vessel. It can also classify the vessel as being in good condition. Three models for object detection YOLO v5, v8, and v10 were trained in this study utilizing pre-processed 640x640 pixel images. The training procedure used an IoU threshold of 0.5, a batch size of 16, and 100 epochs While examining images, YOLO divides each image into a 16 x 16 grid. Within each sector, the model can detect the class if it exceeds 50%. During the testing process, if a single image contains both good and damaged parts or two different types of damage, the model can distinguish between these cases. Google Colab supplied the computing resources for quicker training.

D. Model Evaluation Indicators

The following metrics are used in this work to evaluate the trained YOLO models object identification abilities: precision, recall, mean average precision (mAP), training accuracy and confusion matrix. The best model performance for the task can be chosen more easily according to this comprehensive assessment technique, which provides a more precise understanding of the model's detection ability.

Fig.2. shows Precision Confidence comparison between the three models Yolo v5, v8, and v10. Where precision is a metric that determines the proportion of accurately detected positive occurrences (true positives) out of the total instances projected as positive (true positives and false positives), indicating the accuracy of positive predictions. Precision, equation (1), measures how accurate the positive predictions are:

$$Precision = \frac{Tp}{Tp+Fp} \quad (1)$$

Where
Tp: Number of true positive examples.
Fp: Number of false positive examples.

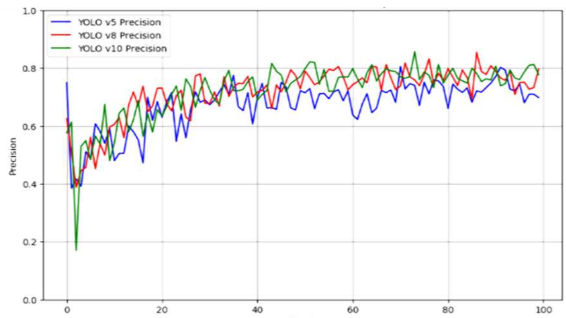


Fig.2. Precision Curves

It demonstrates that the YOLO v8 model's Precision (properly detected positive cases) reached a peak of 84%, indicating its effectiveness in accurate object identification across diverse classes (Good, Corrosion, Brittle Fracture, Mechanical Damage, and Pitting Corrosion).

Fig.3. illustrates the Recall Confidence comparison curve between the three models Yolo v5, v8, and v10, where recall is a statistic that calculates the proportion of correctly detected positive cases (true positives) across all instances (true positives and false negatives). Recall, equation (2), is a metric that concludes the proportion of accurately identified positive cases (true positives) out of the entire cases (true positives and false negatives).

$$Recall = \frac{Tp}{Tp+Fn} \qquad (2)$$

Where
Tp: Number of true positive examples.
Fn: Number of false negative examples.

The curve shows that the YOLO v8 model has a higher recall of 78.5 %. This means that the model was good at finding true positive cases.

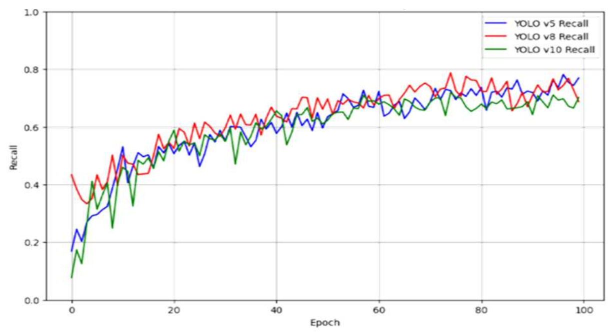


Fig.3. Recall Curves

The relationship between mAP and the number of epochs required to equate the three models' overall detection performance is shown in Fig. 4.

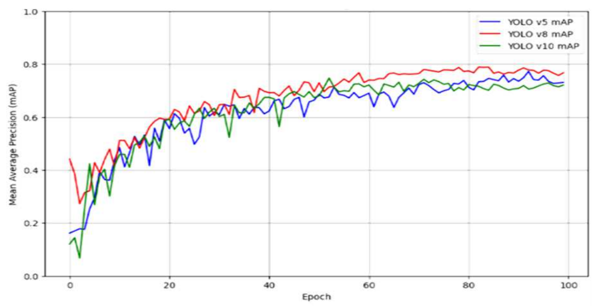


Fig. 4. mAP Curves

where the YOLO v8 model achieved a high mAP of 79 %. As a result, it is a good model that regularly produces correct detections of good or damage mechanism classes. The Mean Average Precision, equation (3), is a metric that quantifies how accurate the model operates in object detection tasks.

$$mAP = \frac{\sum_{K=1}^{N} PR}{N} \qquad (3)$$

Where
N: Number of identified sample classes.
P: Precision, R: Recall

The performance of a trained machine learning model on the training dataset is referred to as training accuracy. Training Accuracy, equation (4), measure of how well the model is learning during the training process

$$Training\ Accuracy = \frac{True\ Positives}{Total\ Samples} \qquad (4)$$

Fig.5. illustrates that the YOLO v8 model achieved the maximum training accuracy of 87%, while the YOLO v5 and YOLO v10 models achieved 80% and 84% training accuracy, respectively.

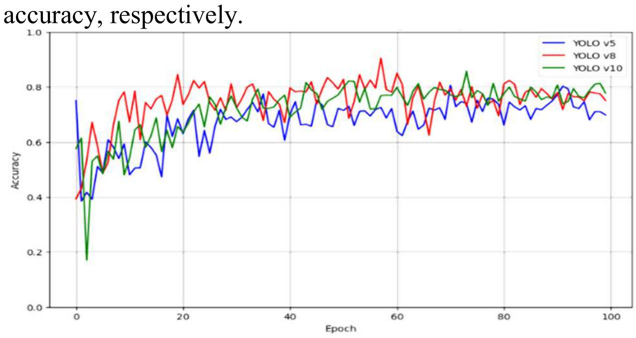


Fig.5. Training Accuracy Curves

The confusion matrix visualizes the model's performance It reveals how many predicts are right (True Positives (Tp) and True Negatives (Tn)) and which are incorrect (False positives (Fp) and False negatives (Fn)). This helped to discover the model's strengths and limitations, allowing it to perform better, and demonstrating the outcomes of the applied confusion matrix of YOLO v8 model. This confusion matrix shows a good act in the Corrosion (0.88 true positive rate), Good (0.84), and Brittle Fracture (0.82) classes, and a good performance in the Mechanical Damage (0.82), Pitting Corrosion (0.41) class, as shown in Fig.6.

IV. TEST RESULTS

The test dataset of Damage Identification Model (DIM) had never been viewed by the DIM. The dataset contained 640x640 pixel JPG photos. The output was divided into five classes: good, corrosion, brittle fracture, mechanical damage, or pitting corrosion. Each of the five classes contained 30 images. Pressure vessels with no damage at all were categorized as "Good", On the other hand, those that had damage were tagged with the correct categories.

This study examined the performance of three YOLO models, YOLO v5, v8, and v10 models, for real-time multiclass detection of internal damage mechanisms in oil and natural gas pressure vessels. The pre-trained weights for the models were evaluated to determine the most accurate and computationally efficient model for this application. YOLO v8 achieved a high detection rate of 93.3%, with 140 images properly classified, and 10 images from the test set remaining undiscovered. No conflict occurs when there are no misclassified photos, as shown in Table II.

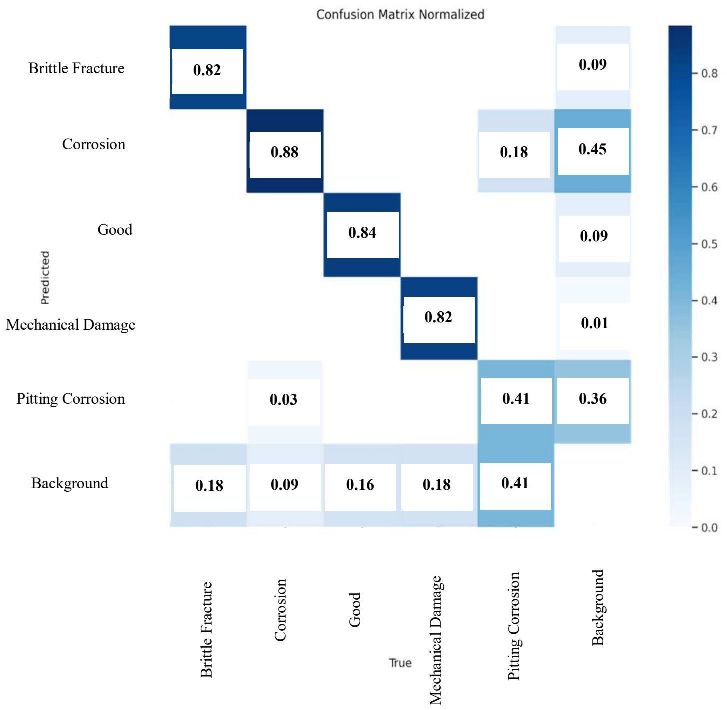


Fig. 6. YOLO v8 Confusion Matrix

TABLE II. EVALUATION OF OBJECT-DETECTING MODELS' PERFORMANCE

Model	No. of correctly detected	No. of not detected	Accuracy
YOLO v5	135	15	90 %
YOLO v8	**140**	**10**	**93.3 %**
YOLO v10	138	12	92 %

V. CONCLUSION

Artificial intelligence (AI) was utilized in this study to detect and identify internal damage of pressure vessel interior shells. This technology was developed to help oil and gas sector avoid the financial consequences of pressure vessel breakdowns. A YOLO v8-based deep learning model was presented in this work to determine if the internal shell of the pressure vessel is damaged or in good condition.. The second author obtained real pressure vessel images on-site at PETROBEL's Abu Madi gas field in Egypt. This data was organized into a dataset, which was then manually tagged to enable supervised learning. The dataset was divided into testing, validation, and training samples.

A computer vision model was developed inside this framework. For damage Identification Model (DIM), this model focuses on detecting the precise type of damage that occurred on a pressure vessel. Leading to multi-class identification of internal damage, DIM is divided between "good" condition and four damage categories; corrosion, brittle fracture, mechanical damage, and pitting corrosion. During testing, the model is able to distinguish between scenarios when a single image has either good and damaged regions or two separate kinds of damage. By using three different versions of YOLO v5, v8, and v10, DIM using YOLO v8 showed a remarkable 93.3% average detection accuracy. This study offers a useful research roadmap for pressure vessel damage detection using image processing in the future.

VI. LIMITATION

The developed model must be accurate and effective in real-time object detection in order to be suitable for use in practical situations. However, the model may have limitations that negatively impact its accuracy and limit its ability to detect objects as expected such as:

- Variations in lighting, angles, and backgrounds can have a substantial impact on model performance.
- Many training datasets may be imbalanced in their depiction of distinct damage types. resulting in weak performance in identifying those particular damages.
- If the threshold is too high, the model may overlook tiny damages, while an indication that is too low may result in false positives, complicating the assessment process.
- Damage with complicated patterns or combinations, might cause the model to become confused.

DATA AVAILABILITY

The datasets obtained and/or analyzed during the current study are not publically available because [The data set contains photographs representing the intellectual property of the inspection sector, Petrobel company, Egypt. Public disclosure is likely to risk the privacy of inspections or inspected equipment.] However, they are available from the associated author upon reasonable request.

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