Equipment Detection based Inspection Robot for Industrial Plants

Mohamed Heshmat[1,2][0000-0002-0153-8131], Yang Gao[3]

[1] University of the West of England, UWE Bristol, UK
[2] Faculty of Science, Sohag University, Sohag, Egypt
[3] Surrey Space Centre, University of Surrey, UK
mohamed.abdelwahab@uwe.ac.uk
yang.gao@surrey.ac.uk

Abstract. Industries move toward the replacement of labours engaged in dangerous tasks with fully automated systems. The sixth sense technology aims at achieving that by integrating different technologies in such a way that enables monitoring of industrial plants and predicting any faults that could happen. One important module of the sixth sense technology is inspection robots. This paper aims at providing the inspection robots with equipment-detection capability, resembling the human inspectors performing the customised inspection for a variety of equipment. The types of equipment, used in this study, are reactor, boiler, pump, isolated pipes, meter gauge, and valves. Given the complexity of the industrial environment, we propose a real-time deep-learning-based equipment detection model. The results show that the mean average precision is above 90%, which ensure the significant performance of the proposed solution. This work validates the practicality of our equipment-detection model and shows its potential to be employed on our inspection robot.

Keywords: Industrial Inspection, Inspection Robot, Equipment Detection.

1 Introduction

Industry 4.0 is transforming industrial processes into complex, smart cyber-physical systems that require intelligent methods to support safer operations. Under these conditions, it is extremely difficult to manage all available information, infer the desired conditions of the plant and take timely decisions to handle abnormal operations [1]. Thus, a technology that could help in preventing human error and stop chain reactions that can transform small incidents into catastrophic failure is required. The sixth sense, 6S technology aims to achieve that need by analysing the present data and generating a vision of the future.

Inspection is the practice of examining the condition of equipment to find out if it operates as intended. The implementation of routine inspection is an essential measure to ensure a safe and efficient production process. For the inspection tasks, checkpoints which mainly include key equipment, pipelines, key valves, gauges, and control points are defined for the inspector. A leak of gas or liquid is searched by sight and smell.

Valves and gauges are examined to understand the operating status of the equipment. For equipment such as pumps, human inspectors need to listen to the sound of their operation or use specific instruments to detect vibration anomalies.

Although these tasks are repetitive and time-consuming, and some of these environments may be hazardous, humans are still relied on for doing these tasks. Long-time close exposure to such environment may cause diseases or even kill in anomalies such as toxic gas leaks and explosions which are not infrequent. Therefore, there is a strong motivation to replace manual inspectors with robots and free them up to perform more complex tasks. On the other hand, manual inspection or operation can be error-prone since human errors are key causes of accidents [2].

Inspector robots can be considered the logical human replacement for doing these tasks. The current robots' capabilities enable these tasks to be carried out efficiently. Examples of these capabilities are autonomous navigation, exploring dangerous or inaccessible sites, a variety of sensors that can be equipped on the robot, quick analysis of sensors data, and relatively lower cost and less time for executing tasks. As the modern plants become larger and more complex, qualified professional's capabilities are required more creative tasks than routine inspections.

In inspecting any site human inspectors are familiar with the equipment and tools that are available on this site, in addition to, equipment history. The 6S framework could provide robots with the required information and history of available equipment. For the inspection tasks, robots need a very basic skill for human inspectors which is detection and identification of available equipment in the environment. The main contribution of this paper can be described as follows: a deep-learning-based equipment-detection method for inspection robots in industrial sites within the vision of industry 4.0 and the 6S technology.

The rest of this paper is structured as follows. Section 2 reviews the previous works in robotic inspection systems. Section 3 explains the 6S technology and the robot inspection strategy. Section 4 shows the deep-learning-based equipment-detection method development and evaluation. Section 5 presents conclusions and future works of this work.

2 Robotic Inspection Literature

In the last decade, there was a growing interest in employing robots for inspection tasks in process plants, due to the compatibility of robots for these tasks. The potential of applying robots for these tasks has been proven [3]. Some projects were funded in this direction such as RoboGasInspector [4], MAINBOT [5], and PETROBOT [6]. The main target for these projects was to develop robotic inspection systems for different industrial environments. In the recent past, Total company organized the ARGOS challenge of creating the first autonomous robot for oil and gas sites [7]. This competition was organized in three rounds. Through these rounds, the robot is required to work autonomously for surveillance tasks. During these rounds, the robot should inspect various visual checkpoints like pressure gauges and valves, and monitor the plant for thermal hot spots, gas leaks and sound signals.

In [8], the authors developed an inspection system to inspect substation equipment. They used a four-wheel robot equipped with a magnetic sensor, RFID reader, pan-tilt camera, lidar sensor, Infrared thermal camera, and directional microphone. The robot follows magnetic markers as checkpoints for the inspection tasks. For this system, checkpoints are needed to be defined for the robot to execute the inspection tasks using the right sensors. We aim at advancing our inspector with a higher perception advantage which is the equipment identification. The importance of that has been demonstrated in [9]. As a result, the inspector robot will not need checkpoints to be defined. The human inspectors can identify equipment types and based on that decide inspection tasks for this type of equipment. For instance, upon detecting a boiler, the inspector ensures that there is no leakage and checks the upper valve state. If a pipe is detected, he checks the pipe visually, especially, the connections and uses the thermal camera to detect the temperature of this pipe. The 6S technology framework keeps track of the history of available equipment and will provide the inspector robots with such information to facilitate inspection tasks. Likewise, the inspector robot will send routine equipment inspection information to the main system, and if a new piece of equipment is detected.

3 System overview

3.1 The industrial 6S

The 6S technology is an intelligent monitoring and control framework for industrial processes, which takes advantage of technological advances such as wireless sensor networks, 5G communication, cooperative control, intelligent decision-making framework, and robotics to ensure stable process operation. The general framework of 6S technology is shown in Fig. 1. Six main modules constitute the structure of this framework. These modules are the holistic system models and cooperative control, massive connectivity resilient network communication, machine learning fault detection and prediction, intelligent adaptive decision-making, virtual reality system, and autonomous inspector robots.

The 6S architecture divides into physical and cyber layers. The physical layer where the industrial process itself, wireless sensors and actuators, physical controllers, and inspector robots are available. In the cyber layer, the wireless communication network, data and models centre, fault detection and prediction algorithms, and decision-making framework are located.

The architecture is designed as a modular architecture. Within the 6S technology, the decision-making framework should make recommendations about the process state to the human operator. Also, it defines the tasks for the inspector robots, normal inspection tasks or other more specific tasks based on the current situation. The main task for the inspector robot is to patrol around the plant to detect abnormal situations (routine inspection) within the vision of 6S technology. The application of the proposed architecture is investigated on a pilot plant that is available at University of Surrey, United Kingdom. Photos of this pilot plant are shown in Fig. 2. These photos show the complex tanged environment where the robots work.

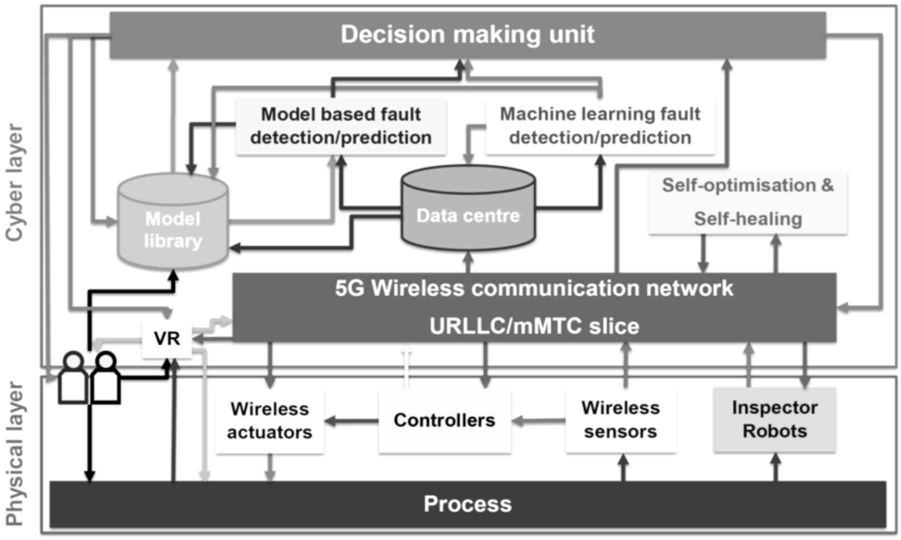

Fig. 1. The 6S technology framework

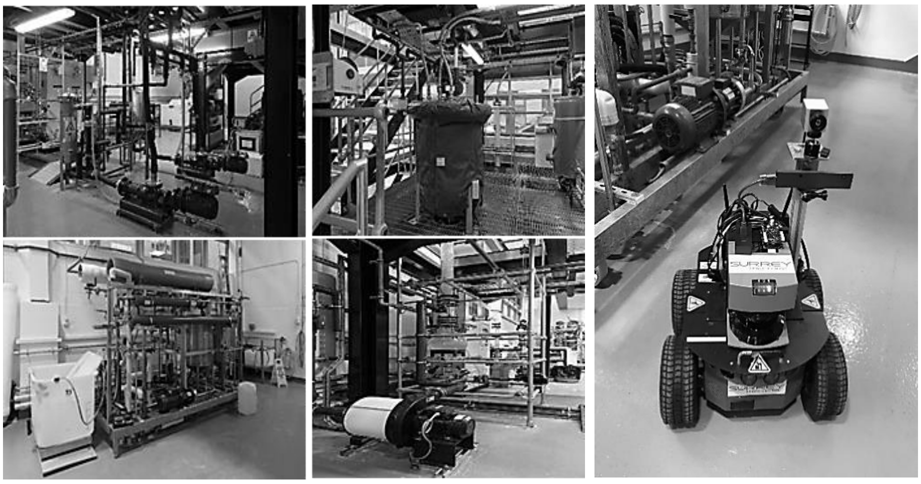

Fig. 2. The pilot plant photos on the left and the inspector robot for industrial sites on the right.

3.2 The Inspection Strategy

Our inspector robot is a small four-wheel Pioneer 3-AT mobile robot equipped with an RGBD camera, 2D laser range finder, infrared camera, acoustic & gas sensors board as shown in (Fig.2). These sensors were selected based on their suitability for inspection tasks in this environment. The robot size is chosen to be suitable for the inspection application in small and medium industrial processes, as the robot may need to maneuver around equipment and pipes which are, usually, available in this environment.

In the current state of periodic inspection tasks of industrial sites, the human inspectors could perform these tasks with a degree of efficiency, but these tasks are repetitive, the environment itself could be hazardous, and in the end, errors still could happen. Therefore, the need for inspector robots became clear. The current robots' systems able to fill human inspector duties efficiently.

In inspecting any site, human inspectors are familiar with the equipment and tools available on this site in addition to the history behind each piece of equipment. The 6S framework could do this role and provide the robots with information and history about available equipment. One skill still the robots need to be equipped with to be able to do inspection tasks is the identification of the available equipment in the environment.

As a general system is targeted, solely defining the equipment positions is not sufficient for the robot to do the inspection tasks. Also, these sites are, usually, dynamic environments and a lot of equipment could be added or removed from the site. Thus, the inspector robots need to be equipped with this capability to execute these tasks efficiently. Moreover, the inspector robots may need to interact and integrate with other human inspectors if they are available. Consequently, they need to have the same philosophy of doing the inspection tasks which make the interaction much easier.

For our inspection strategy hierarchy, the first task is the detection of equipment type. Six types of equipment are investigated in this study and these pieces of equipment are available in our pilot plant environment where our robot will be tested. Based on the equipment type, the robot decides the required inspection task list to be carried out. Each type of equipment requires different sensors to be used and different inspection checklists to be executed. These types of equipment are reactor, boiler, pump, isolated pipes, meter gauge, and valves.

Table 1 summarizes the inspection checklist for each equipment type. Inspired by the human inspector, the robot will begin any inspection task by collecting information history of this piece of equipment from the 6S main system. The 6S framework supplies the robot with information about the equipment previous status, maintenance history, and normal working condition. This information will differ from one to another and will support the robots in proceeding with their tasks and detecting anomalous conditions. Later, the robots will forward their inspection data to the main 6S framework for records.

4 Equipment Detection

4.1 Development

For an equipment-detection based robotic inspection system, a real-time solution is needed to fulfil task necessity. The object detection process includes the classification and localization of objects in the image. Single-shot object detectors which take one shot to detect objects that are presented in the image are considered appropriate in the context. These algorithms are fast and high-accurate object detection algorithms. From these algorithms, we selected the You Only Look Once, YOLO algorithm [10].

Table 1. Equipment Inspection checklist.

Equipment	Checklist
Reactor	- Get history information from the 6S main system - Check the pipes and the pump that are usually attached - Check the body with the IR camera
Boiler	- Get history information from the 6S main system - Check the pipes and the valve that are usually attached - Check the body with the IR camera
Isolated Pipe	- Get history information from the 6S main system - Check the pipe with IR camera especially the connections
Pump	- Get history information from the 6S main system - Check the body with the IR camera - Check the sound with the acoustic sensor
Meter Gauge	- Get history information from the 6S main system - Read the gauge measurement value
Valve	- Get history information from the 6S main system - Detect the valve state (Open or Closed)

YOLO is considered the state of art object detection, single-shot algorithm. It is a real-time object detection that is developed for object detection of camera images. It consists of a single convolutional network that simultaneously predicts multiple objects with class probabilities for those objects. YOLO trains on full images and, directly optimises detection performance. The YOLO algorithm detects, classifies, and identifies objects in the image frame and draw a rectangular bounding box around it. Through this work, the darknet YOLO v3 framework has been used. The darknet is an open-source neural network framework written in C and CUDA [11].

The development work was conducted in three stages, dataset collection, training, and validation. The dataset collection has two purposes: a collection and annotation of the equipment image dataset at University of Surrey pilot plant. After human visual inspection of images and confirmation of their correctness and quality, these images were annotated manually. The dataset was split into training and validation datasets. The whole dataset was 1267 images, the training dataset was 80% of the original dataset, and the validation dataset was the remaining 20%. Visual inspection of the resulting datasets reveals multiple challenges associated such as blurring, scale variation, occlusion, and background clutter.

To accelerate the training process, we used partial pre-trained weights as the initial training model [12]. The training process was carried out using GPU (GeForce GTX 1050) and Intel Core i7 2.8 GHz CPU. During the training process, loss function was monitored all the time. YOLO uses the sum-squared error between predictions and ground truth to calculate the loss value. The loss function composes of classification loss, localization loss (errors between predicted boundary box and ground truth), and confidence loss. The final loss value is the sum of these values.

The validation process takes place, using the validation dataset, periodically during the training process. The trained model should achieve an appropriate accuracy for the intended task, and so the PASCAL VOC evaluation metrics are used, to evaluate the classification and localization performance of the equipment detection model [13]. The first of these metrics is detection precision, which is calculated as the ratio between the number of positive samples correctly classified to the total number of samples classified as positive (either correctly or incorrectly). The precision measures the model's accuracy in classifying a sample as positive. Second, the detection recall, which is calculated as the ratio between the number of positive samples correctly classified as positive to the total number of positive samples. The recall measures the model's ability to detect positive samples. Third, the intersection-over-union (IoU), which represents the intersection over the union of objects and detections for a certain detection confidence threshold.

Average precision (AP) is another popular evaluation metric in measuring the accuracy of object detectors. AP can be defined as the average of maximum precision at different recalls. Mean average precision (mAP), which is used to evaluate the validation process, is defined as the average of APs over all classes. Another evaluation metric that is investigated in this work $F1_{score}$. The $F1_{score}$ is another measure of model accuracy, it considers both precision and recall of the model to compute the score. It represents the harmonic mean of the precision and recall, where an $F1_{score}$ reaches its best value at 1 (perfect precision and recall) and worst at 0.

$$F1_{score} = \frac{(Precision \, * \, Recall)}{(Precision \, + \, Recall)} \tag{1}$$

4.2 Evaluation

To validate and monitor detector performance, mAP was periodically calculated using the validation dataset during the training process. This helps ensure that the detector maintains global performance during training without overfitting or underfitting problems. Overfitting is where a model learns the training dataset too well, performing well on the training dataset but does not perform well on a holdout sample. On the opposite, underfitting is where a model fails to sufficiently learn the problem and performs poorly even on a training dataset.

The threshold of object bounding boxes confidence is an important parameter to tune for better object detection. The confidence threshold is defined as IoU between the predicted box and the ground truth. a confidence threshold of 50% means that we will accept proposals that believe their bounding boxes have more than 50% overlap with a real object. The increased confidence threshold leads to fewer bounding box proposals for each image. The decrease in the confidence threshold results in more bounding boxes.

Figure 3 shows the training loss value and validation mAP percentage over 12000 iterations. The validation mAP was computed over periods of training iterations. The minimal variation in loss during training as well as steady convergence to a small number (0.0875) shows that the optimiser was able to find the global minimum of the loss function. The validation of this model shows accurate detection with (91.6%) mAP. Also, from Fig. 3, we can observe that the use of a partial pre-trained initial model helped the neural network to converge very quickly.

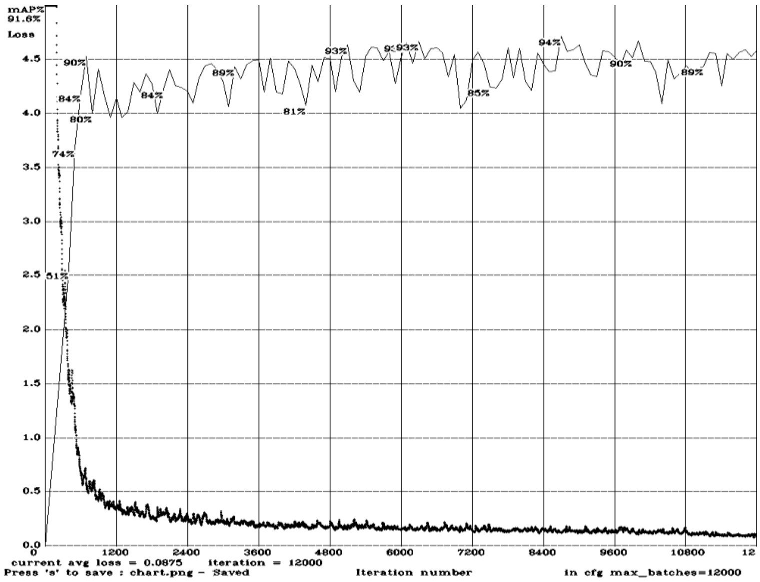

Fig. 3. The training loss and validation mAP of the equipment detection model.

Table 2 summarizes the evaluation details for each class and the whole model in general. The general model evaluations have been done on Confidence = 0.50. The evaluation results show 0.96 precision which shows the recognisable consistency of our model. The 0.86 recall result shows that our model can mostly return the relevant results. The F1score combines the precision and recall of the model. The result F1score = 0.91 reflects the robustness of the detector overall performance. The predicted bounding boxes overlapping with the ground truth is shown with IoU = 78.09%, which means that that the predicted and ground truth bounding boxes almost overlap. The evaluation metrics show the accuracy of our model for detecting equipment in the industrial environment.

Table 2. Equipment detection evaluations.

Equipment	**AP**	**True Positive**	**False Positive**
Reactor	81.08%	27	3
Boiler	93.48%	62	3
Isolated Pipe	86.35%	170	11
Pump	99.43%	119	2
Meter Gauge	99.74%	121	2
Valve	89.53%	230	8
General Model Evaluation (Confidence = 0.50)			
Precision = 0.96	Recall = 0.86	$F1_{score}$ = 0.91	IoU = 78.09%

The resulting evaluation of the model shows a promising accuracy in detecting different types of equipment in this difficult environment. The relatively low performance in the reactor and isolated pipes cases is due to the following reasons. The reactor case had the least amount of training data, so it needs more training data under various conditions. On the other side, although the case of the isolated pipes has the second-highest training data, it represents a very complex model to be learned as the isolated pipes can have different sizes and shapes. Also, various other objects, which are usually available in the industrial environment, could easily be misclassified as isolated pipes.

Fig. 4. Shows the model qualitative results. These results show the accuracy and generalization of our model. Despite the equipment having different sizes, scales, and tangled together, our model could correctly detect the equipment available in the input images. We have tested the model for real-time equipment detection operation at the pilot plant. The recorded video shows the equipment detection capability of the model, and it could achieve more than 10 frames per second. Videos of the Industrial Robotic Inspector and the real-time equipment detection model testing is available[1].

5 Conclusions

A deep-learning-based solution for real-time equipment-detection-based inspection robotic system has been proposed for industrial plants within the vision of industry 4.0. The robotic inspection module is part of the sixth sense technology framework, which aims at monitoring the industrial plants to ensure their safety.

The development phase of the proposed solution has involved dataset collection and annotation and then training, validation, and testing of the model. This study has proposed an equipment-detection model based on the Darknet YOLO framework. The model has been carefully developed to consider the accuracy and real-time operational requirements. The trained model has evaluated, and its capabilities have been shown. The quantitative and qualitative results of the model evaluation have shown the accuracy of the equipment-detection model.

In the future, more types of equipment will be incorporated into our model using transfer learning techniques. Also, the sub-inspection tasks include valve state detection (video of visual valve state detection is available[2]), meter gauge reading, acoustic sensing, gas sensing, and thermal sensing are going to be accomplished subsequently. Eventually, we can test our inspection robot for undertaking the routine inspection at our pilot plant.

---

[1] https://www.youtube.com/watch?v=-w1_LDqRJfk
https://www.youtube.com/watch?v=UDelE65qZzs

[2] https://www.youtube.com/watch?v=9URzc8RUnyo

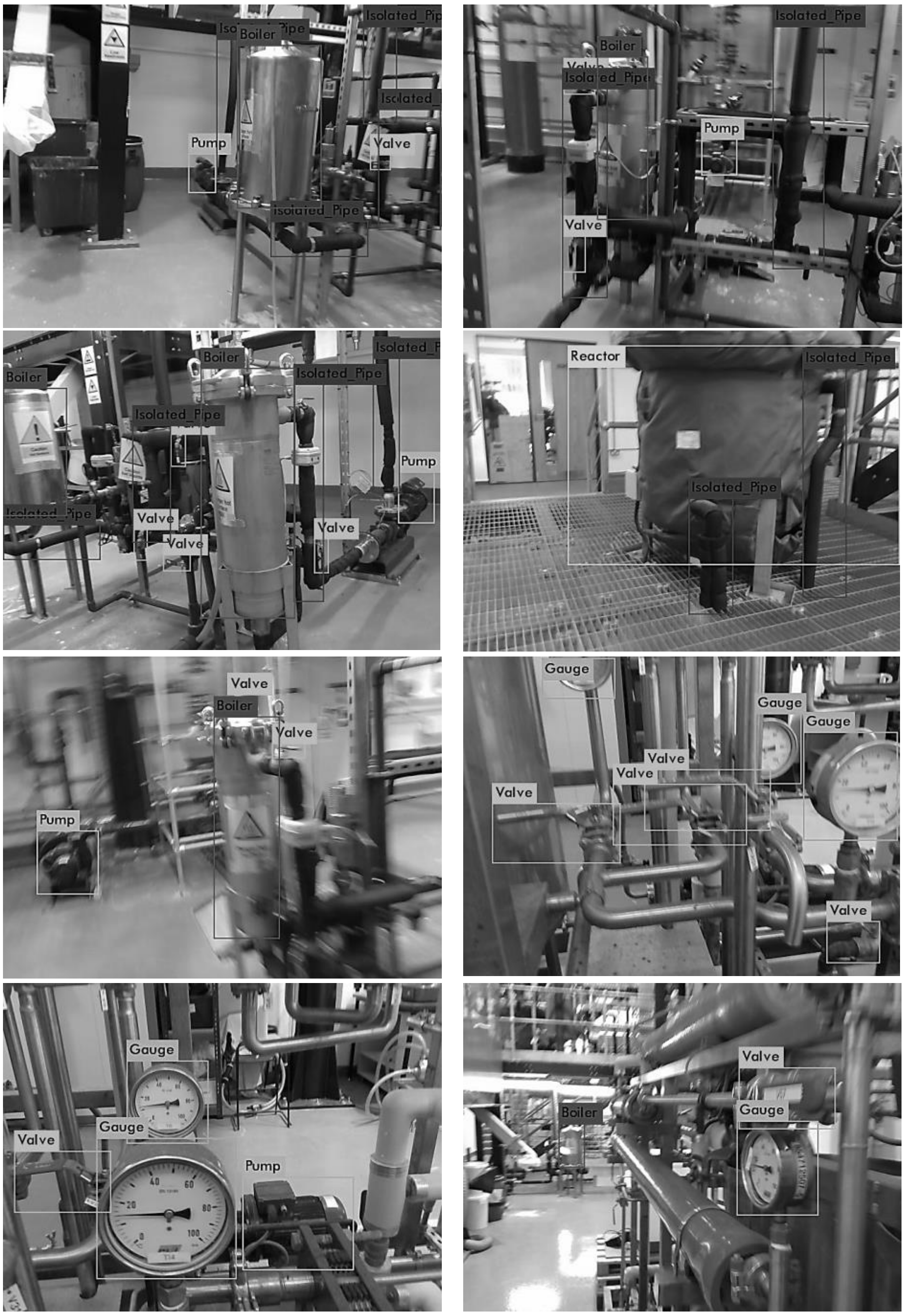

Fig. 4. Qualitative results of the equipment detection for robotic industrial inspection

References

1. Sathish Natarajan, Rajagopalan Srinivasan.: Implementation of multi-agents based system for process supervision. *Computers and Chemical Engineering*, vol. 60, pp. 182-196, (2014).
2. Marilia Abílio Ramos, Enrique López Droguett, Ali Mosleh, Márcio das Chagas Moura, Marcelo Ramos Martins.: Revisiting past refinery accidents from a human reliability analysis perspective: The BP Texas City and the Chevron Richmond accidents. *The Canadian Journal of Chemical Engineering*, vol. 95, pp. 2293-2305, (2017).
3. Matthias Bengel, Kai Pfeiffer, Birgit Graf, Alexander Bubeck, Alexander Verl.: Mobile robots for offshore inspection and manipulation. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, (2009).
4. Samuel Soldan, Gero Bonow, Andreas Kroll.: RoboGasInspector - A Mobile Robotic System for Remote Leak Sensing and Localization in Large Industrial Environments: Overview and First Results. *IFAC Proceedings Volumes*, vol. 45, no. 8, pp. 33-38, (2012).
5. I. Maurtua, L. Susperregi, A. Fernández, C. Tubío, C. Perez, J. Rodríguez, T. Felsch, M. Ghrissi.: MAINBOT – Mobile Robots for Inspection and Maintenance in Extensive Industrial Plants. *Energy Procedia*, vol. 49, (2014).
6. Barend Van den Bos, Joakim Strand, Adam Mallion, Moritz Oetiker, Andreas Schler, Timothy Black, Prashant Potnis.: Robotic Inspection Solutions for Petrochemical Pressure Vessels, developed and tested in the PETROBOT project. *World Conference on Non-Destructive Testing*, (2016).
7. ARGOS Robotics Competition Website, https://www.total.com/dossiers/argos-challenge-building-tomorrows-oil-and-gas-robot, last accessed 01/05/2021.
8. Haojie Zhang, Bo Su, Hong Meng.: Development and implementation of a robotic inspection system for power substations. *Industrial Robot*, vol. 44, no. 3, pp. 333-342, (2017).
9. Affan Shaukat, Yang Gao, Jeffrey A. Kuo, Bob A. Bowen and Paul E. Mort.: Visual Classification of Waste Material for Nuclear Decommissioning, *Robotics and Autonomous Systems*, vol. 75, pp. 365-378, 2016.
10. Redmon, Joseph and Farhadi, Ali.: YOLOv3: An Incremental Improvement. arXiv, (2018).
11. J. Redmon.: Darknet: Open Source Neural Networks in C. http://pjreddie.com/darknet/, last accessed 01/05/2021.
12. Hsieh, Chien-Yao Wang and Hong-Yuan Mark Liao and I-Hau Yeh and Yueh-Hua Wu and Ping-Yang Chen and Jun-Wei.: CSPNet: A New Backbone that can Enhance Learning Capability of CNN. *arXiv,(*2019).
13. Mark Everingham, Luc Van Gool, Christopher K. I. Williams, John Winn, Andrew Zisserman.: The PASCAL Visual Object Classes (VOC) Challenge. *International Journal of Computer Vision, (*2010).