Image-Based Underwater Liquid Leak Detection and Transfer Learning

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This paper addresses the critical challenge of liquid leaks in the oil and gas industry by leveraging advanced computer vision and deep learning methodologies. The objective is to develop practical models for detecting underwater objects with low image quality in adverse conditions. We train and test CNN detectors using Facebook's Detectron2 Faster R-CNN. The model was evaluated on a custom dataset of underwater oil spill videos, focusing on detection accuracy and processing speed. The results demonstrated that even using images of smoke in the sky as training made it possible to detect the underwater oil leak accurately.
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The offshore oil and gas industry is one of the most profitable industries in the world. However, due to the nature of its deep subsea operations, these industries could face some issues, such as safety concerns and environmental impact. Such issues can directly impact enterprise profit and generate life risk. Machinery fluid and crude oil leakages are examples of issues that can affect the external environment and normal operation conditions. Several studies have tried to address the task of underwater leakage detection.

Most of them use acoustic sensors, fluorimeters, and vibration sensors to obtain the data post-processed by a machine or deep learning algorithm to extract and analyze patterns indicating the presence of leakages; these methods can be inaccurate and relatively expensive [1]. Underwater object detection is generally achieved by sonar, laser, and cameras. Compared to sonar and laser, the cameras are low-cost and can capture more visual information with high temporal and spatial resolution.

Our proposal in this work is to offer an accurate and cost-efficient solution for underwater leak detection using imaging and deep learning techniques. By incorporating the Faster Region-based CNN (Faster R-CNN) [2] models, we aim to enhance the identification capability of liquid leaks in key infrastructure components. Harsh underwater environments negatively impact methods that rely on edge information by reducing object detection accuracy. Convolutional neural networks (CNNs) dominate current object detection research to improve detection speed and accuracy. CNN-based methods can be divided into two main categories: Region Proposal-Based Frameworks(two-stage) and Regression/Classification-Based Frameworks(one-stage).

Object detection is one of the tasks of computer vision, where the goal is to recognize objects and locate them in an image. Deep learning models can recognize and extract information from images in challenging environments while simultaneously working with vast data.

Underwater object detection is generally achieved by sonar, laser, and cameras. Compared to sonar and laser, the cameras are low-cost and can capture more visual information with high temporal and spatial resolution. Underwater leak detection using deep learning is an active and rapidly evolving field of research, with some published studies on this topic, such as Bansod [3] that describe the use of thermal images to enhance leak identification by deep neural and Rehman [4] that address the topic of using sensor signals as input along with images to create an attention-based model.

Various studies have tried to solve the leakage detection task using object detectors. Going in the opposite direction, the paper written by Padovese

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[5] uses a Passive Acoustic Monitoring (PAM) system for leakage detection on offshore CO_2 geological storages. It takes advantage of the signal disturbance caused by the emission of bubbles to classify the acoustic signal and detect gas leakage.

The main benefit of PAM use is the investment cost of sensor equipment and the extended range of the sensor. However, this system could not detect fluid leakage on offshore equipment located in the seabed. PAM sensors can be affected by other sources of signal (noise), which introduces complexity to the detection task. Beyond that, passive acoustic is mainly used in wildlife studies.

Traditional sensors face significant challenges in high-pressure environments, such as deep ocean ones. These sensors are not low-cost, and the detection complexity increases due to adverse conditions. Other works carried out research in leak detection underwater using deep learning based on pressure measurements, integration of surveillance thermal cameras, and sound and vibration sensors.

As a positive point, these techniques improve the data available for training deep learning models. From another perspective, using sensors can increase investment costs, in addition to the fact that these tools can be inaccurate and fail in specific scenarios of high pressure, such as deep water. The present study proposes an innovative solution based on deep learning and object detection using only underwater images, without the need for vibration, sound, or pressure sensors. This approach offers cost reduction and several advantages compared to related works. Using cameras and deep learning eliminates the need for expensive and sophisticated sensors, such as acoustic and pressure sensors, resulting in a significantly more economical solution. Deep learning models can quickly process large volumes of image data, enabling real-time or near-real-time leak detection, which is crucial for rapid interventions.

Materials and Methods

Next, we present deep-learning models utilized in our study, explain the training and test pipelines, and introduce an augmentation technique to overcome the lack of accurate data representing the underwater scenario with wildfire smoke.

Alternatively, images of wildfire smoke and crude oil leaking that share similar features to underwater leakage have become data to train the AI models. It is done because deep learning models require an extensive data set to achieve good results and generalization capabilities. Due to this lack of data, obtaining evaluation metrics with expressive results is a great challenge, especially in real scenarios.

The algorithms for object detection are based on supervised learning, which requires image samples with objects to be detected and their corresponding bounding boxes represented as labels. Similarly, the leak detection model needs videos or images of comparable liquid leaks in different scenarios for training. The wildfire smoke dataset, consisting of 737 images and annotations, was used to train the models. This dataset was selected because it contains properties and characteristics like liquid leaks. It becomes a quick and cheap solution to overcome the lack of liquid leak data under the sea. Figure 1 shows a frame extracted from the dataset.

After preparing the source data by applying a set of transformations, the total number of images has been split into 3 groups: training, validation, and test. The first two are used during the learning stage of the deep neural network; the training set provides the data distribution from where the model will learn, while the validation one is used to check how well the model evolves its training. Once the training stage is finished, the model weights learned during this phase are used to make inferences on the test set to verify the model performance. Its performance is measured using a mean Average Precision mAP metric based on three metrics: Intersection-over-Union (IoU), Recall, and Precision. The IoU role is to define if a predicted bounding box is a true positive or a false positive by defining a threshold. Boxes with IoU values that fall below that range are considered false, and the ones above are considered valid. Generally, the higher the IoU

Figure 1. Sample of wildfire smoke frame.

threshold, the more challenging the detection task. IoU is computed by dividing the area of overlap by the total union area, subsequently, with the computation of false positives, true positives, and false negatives. Recall and Precision are measured. These metrics measure how well the model is to predict accurate positive samples and how precise the model detections are, respectively. So, the computed value of those two metrics is used to plot the precision-recall curve from where the map will be calculated. Two proofs of concept (POC) were created where one used training only from the wildfire smoke dataset (Only smokesmoke) and another used (Transfer Learning) with the addition of underwater oil spill frames. Both POCs were evaluated on another set of underwater oil spill images (Figure 2).

Results and Discussion

The computer vision community created the mean average precision (mAP) metric to evaluate the efficiency of an object detection model and compare its performance against other models. A high Average Precision (AP) means the model has a low false negative rate and a low false positive rate. A false negative occurs when the model infers the object as a region that is part of the image's background. A false positive occurs when a background region is mistakenly identified as an object. The higher the map, the more accurate and with more excellent recall the model will be. Accuracy measures the proportion of correct samples predicted as positive (correct inference), that is, how often the model predicts correctly. Recall measures the proportion of positive samples obtained from the total existing samples, both samples that were correctly detected and those that were not detected. In other words, how many positive samples could the model find in the total number of existing predictions? In other words, the model predicted every time it should have predicted. The mAP combines precision and recall into a single metric. It measures how accurately the model identifies objects by comparing the predicted bounding boxes' Intersection over Union (IoU) with the ground truth bounding boxes. IoU values are calculated for a range of threshold values, from 0.5 to 0.95, with a step of 0.05. The Average Precision (AP) is then calculated from these IoU values, and the mAP value is the average AP value of all detected classes. A higher IoU value closer to 1 indicates better detection quality (Table 1).

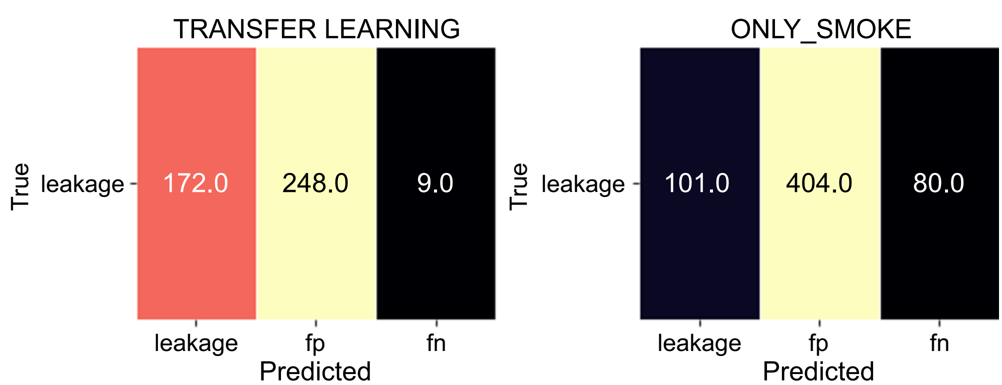
In Figure 3, we present underwater leak detection results for different implementations of the POCs carried out on the same custom test dataset. In machine learning, specifically statistical

Figure 2. Sample of oil spill frame used in transfer learning model train.

Table 1. mAP values for the developed POCs.

Model	mAP 50	mAP 50-95
Transfer Learning	91.41	31.28
Only Smoke	13.09	2.89

Figure 3. Confusion matrix to compare prediction results.



classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically supervised learning. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class, or vice versa. View the confusion matrices of the most promising POCs in Figure 3.

These results in Figure 4 suggest that the TRANSFER LEARNING model outperforms the ONLY SMOKE model in detecting oil leaks, mainly due to its high recall, indicating it captures most true leaks. TRANSFER LEARNING exhibits a higher precision (0.41) and a significantly higher recall (0.95) compared to ONLY SMOKE, resulting in a superior F1-Score (0.57 *vs.* 0.29). ONLY SMOKE has a considerably low precision (0.20), indicating a high number of false positives and a moderate recall (0.56).

The precision-recall curve presented illustrates the performance comparison between two models, Transfer Learning and Only Smoke in detecting oil leaks. The Transfer Learning model demonstrates superior performance in terms of precision across various levels of recall compared to the Only Smoke model. Figure 5 compares the detections with the models in a specific frame. This shows the efficiency and precision in generating the bounding boxes, mainly for the model frame trained with transfer learning. View all inference results in the drive.

Conclusion

In this study, we introduced an approach to underwater liquid leak detection using image-based techniques and transfer learning. Our model significantly improved detection accuracy and

Figure 4. Precision *vs*. Recall curves.

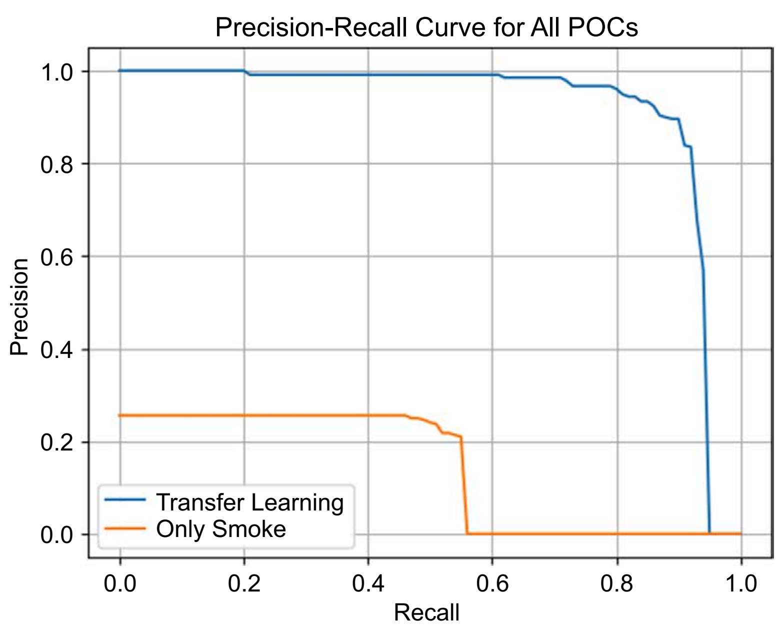


Figure 5. Detection for Transfer Learning model.

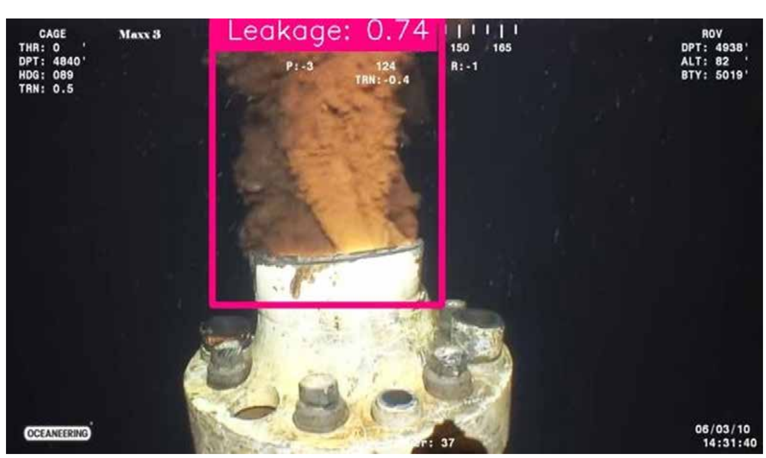


Figure 6. Detection for Only Smoke model.

processing speed by leveraging Faster R-CNN and training on a custom dataset of underwater oil spill videos and wildfire smoke images. The transfer learning model outperformed the single-source model, demonstrating superior precision and recall. This research highlights the potential of deep learning in providing cost-effective, efficient, and real-time leak detection solutions, offering a viable alternative to traditional, sensor-based methods. Future work should focus on refining models and expanding datasets for enhanced robustness.

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