

Unraveling Improvements in Underwater Leak Detection Using Color Channel Operations

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This paper presents a computer vision approach for detecting underwater liquid leaks in the oil and gas industry, focusing on scenarios with limited datasets. We propose the use of color indices—originally developed for vegetation studies, such as ExGR and CIVE—as preprocessing to enhance visual contrast and improve deep learning performance. A custom dataset of 240 simulated leak images, captured in an aquarium under blue lighting, was processed using ExGR, CIVE, and a modified CIVE index developed in this study. The YOLO12n model was trained and evaluated across these configurations. Results show that the modified CIVE index achieved the highest accuracy, surpassing RGB and other indices, with notable gains in mAP. These findings demonstrate that combining tailored color indices with lightweight object detection models can enhance leak identification under adverse conditions, offering a cost-effective and efficient solution for environmental monitoring and operational safety.

Keywords: Leak Detection. Computer Vision. Color Indices. Oil and Gas Industry.

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 risks. Machinery fluid leakages are examples of issues that can affect the external environment and normal operation conditions.

Subsea leak detection has traditionally been carried out using sensor-based methods, such as acoustic systems [1,2], fluorometers and sonars [3], thermal cameras, lasers [4], pressure sensors, and vibration sensors. However, their effectiveness is affected by environmental noise, inadequate sensor positioning, and difficulties in detecting small leaks [5]. Fluorometers, for example, are capable of detecting specific substances dissolved or suspended in water, but they have limited performance in environments with high background fluorescence and may suffer from sensitivity degradation over time [3].

In recent years, camera-based methods have gained prominence [6] due to their relatively low cost, high spatial and temporal resolution, and ability to capture rich visual information. With the advancement of computer vision, deep learning techniques have been applied to detect leaks from underwater images [7]. However, these techniques face a key limitation: the scarcity of suitable datasets. Collecting real-world subsea leak imagery is costly and logistically complex, resulting in small, highly variable datasets that hinder the training of robust neural networks [8]. This constraint affects the training of deep neural networks, which require a large volume and diversity of samples to generalize well in real-world scenarios.

One strategy to optimize learning and reduce this dependency is image preprocessing using color indices. These indices, based on the RGB color space, transform the input image into a single-channel representation where green vegetation is enhanced, simplifying the identification task for the neural network and improving detection performance in many cases. Most of them target using Image enhancement, color correction, image dehazing [9] to obtain the data that then is post processed by deep learning models to extract patterns indicating presence of leakages.

This work proposes the application of color indices widely documented in the literature as a

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strategy for underwater leak detection, aiming to mitigate the constraints arising from the limited availability of data. For the validation of the proposed approach, images of simulated leaks in a controlled environment (aquarium) were used, which were processed and analyzed using the YOLO12n[10] detection model.

Related Works

Several color indices have been proposed in the literature to enhance the segmentation of regions of interest, especially for distinguishing vegetation from soil in agricultural images. The Excess Green Index (ExG) [11], for example, amplifies the green component in the image, producing high-contrast representations that facilitate segmentation. Other indices, such as the Color Index of Vegetation Extraction (CIVE) [12], were derived through statistical optimization to maximize the separation between vegetation and background. To improve robustness, variations such as ExGR [13] have emerged, which reduce false positives by suppressing yellowish debris, as well as MExG [14] and VEG [15], which are designed to be more consistent under varying lighting conditions — a common challenge in open-field environments.

Using a color indice as input to a CNN instead of the traditional RGB image represents an approach that provides a strategic advantage to the detection model, especially in cases of limited datasets. This technique converts the image into a single channel where vegetation is already highlighted, allowing the network to focus on learning more complex morphological features such as leaf shape and texture, rather than expending resources to separate the plant from the background. For instance, Milioto and colleagues [16] fed a lightweight encoder-decoder network with only the ExG index to perform real-time crop and weed segmentation. Similarly, Silva and colleagues [17] used ExGR as the sole input to a CNN for maize plant detection. In both cases, simplifying the input resulted in lighter and faster models, optimized for practical applications that

require high computational efficiency.

Beyond the complete replacement of RGB, color indices can also be used to enrich the input data or to increase model robustness in field conditions. Kerim and colleagues [18], for example, demonstrated that adding CIVE as an extra channel to an input image (along with RGB and other indices) improved the performance of a U-Net network in rice field segmentation, compared to using only RGB. These approaches show that, whether by simplifying or enriching input data, color indices are versatile and promising tools for optimizing neural network performance in detection tasks.

Materials and Methods

A series of experiments was conducted to evaluate how different input configurations influence object detection performance using the YOLO12n model.

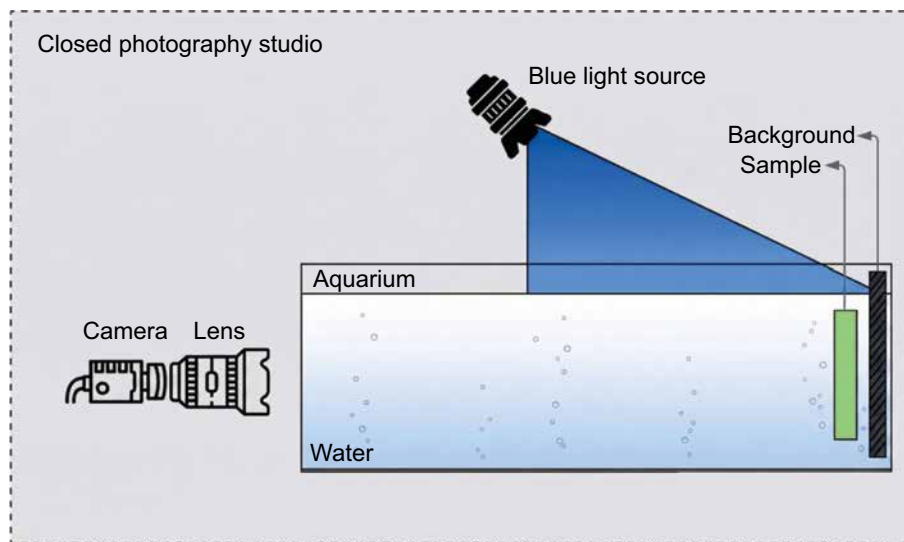
To improve the efficiency of the training and inference processes, we adopted YOLO Nano[10] (YOLO12n model), a lightweight version of the YOLO architecture specifically designed for real-time applications and deployment in environments with limited computational resources. Despite its compact size and reduced number of parameters, YOLO Nano maintained competitive detection performance, demonstrating its suitability for the task of leak identification. Its architecture is optimized to balance accuracy and speed, making it a practical choice for scenarios where latency and hardware constraints are critical.

The experiments were conducted under four main configurations: (i) training with RGB images (baseline); (ii) training using the ExGR color indice; (iii) training with the CIVE color indice; and (iv) training with a modified version of the CIVE indice, developed in this work to enhance the visibility of leaks in the samples. The Table 1 shows the color indices formulas with the coefficients used for experimentation.

An experimental setup was created to simulate an aquatic environment, as shown in Figure 1. Using a water-filled aquarium, a camera is positioned

Table 1. Color ratio index.

Index	Formula
CIVE	$0.441R - 0.811G + 0.385B + 18.78745$
CIVE (ours)	$0.141R - 0.111G + 0.185B + 1.78745$
ExGR	$(2G - R - B) - (1.3R - G)$

Figure 1. Laboratory setup for tests.

toward the aquarium, which has a background to aid visualization. Additionally, a light source is positioned to illuminate the environment with a selected color—in this case, blue.

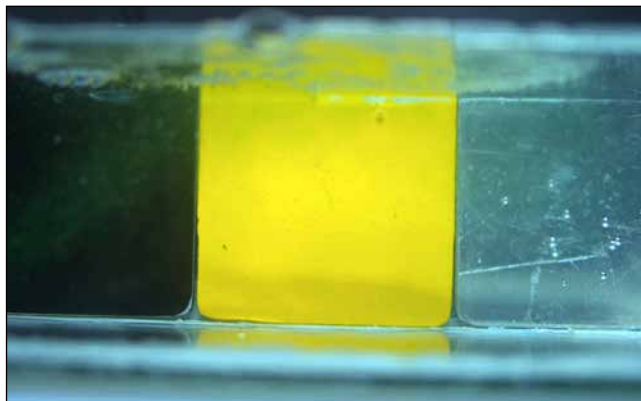
The use of blue light was chosen because it enhances the identification of the color green, as green objects exhibit high reflectance in this spectral range, resulting in greater contrast compared to other surfaces. In an underwater environment, this choice is even more relevant since water quickly absorbs longer wavelengths, better preserving blue light and, consequently, the visual distinction of green targets [19].

Dataset

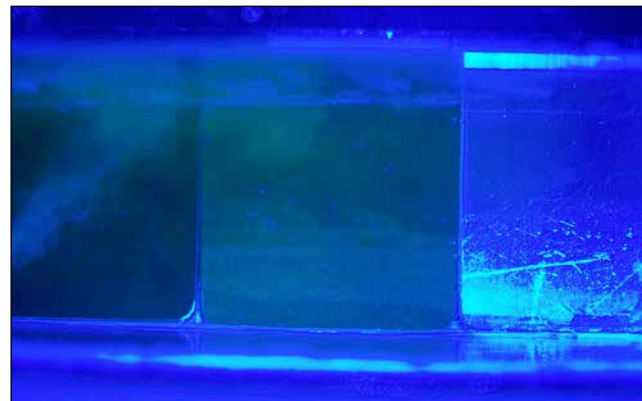
The dataset used in the experiments consists of 240 annotated images, each containing bounding boxes that delineate the objects of interest. The

images were randomly split into three subsets: 144 samples for training, 36 for validation, and 60 for testing. Prior to training, all images were resized to 640×640 pixels, maintaining their original aspect ratio to ensure consistency across inputs. Figure 2 (a) shows an example of an aquarium environment using white light for illumination. The use of blue light offers several advantages in the context of visual analysis and computer vision. Blue light enhances the contrast of certain surface textures and materials, particularly in cases where defects, edges, or fluid residues may be subtle under standard white light. This characteristic helps to accentuate features that are otherwise difficult to detect, improving the signal-to-noise ratio in the image and highlighting relevant regions for object detection. It is possible to see in Figure 2 (b), where the experimental environment is illuminated with blue light.

Figure 2. Comparison of samples under different lighting conditions.



(a) Sample with white light.



(a) Sample with blue light.

Images generated through index calculation and channel stacking offer alternative representations that can emphasize specific visual properties not always evident in standard RGB formats. In the case of index-based images, a mathematical formula is applied to the original RGB channels to produce a single-channel grayscale image that highlights particular features. These single-channel images were then resized and normalized to be compatible with the YOLO12n model's input requirements, enabling the network to learn from a condensed yet feature-rich representation of the scene.

For the channel-stacked configuration, a hybrid image was created by replacing the red (R) channel with the index map while retaining the original green (G) and blue (B) channels. This approach aimed to preserve the spatial and chromatic context of the original image while injecting the enhanced discriminatory power of the color indices. This type of input is particularly useful in applications where certain features are more salient in transformed domains than in raw RGB space.

To select the most suitable indices for visually enhancing leak detection, different color indices documented in the literature were evaluated based on their ability to highlight leak regions against the background. Among the tested indices, CIVE and ExGR exhibited the most pronounced visual contrast, making them the main candidates for experimentation. The ExGR and CIVE indices

were selected for demonstrating a high capability to isolate leak areas from the surrounding structures.

Training

The training process is carried out using the YOLO12n model, initialized with COCO-pretrained weights [20]. Each variant is trained for 100 epochs, with an image size of 640×640 pixels and a batch size of 16 samples. The experiments are performed on a workstation equipped with an NVIDIA RTX 3060 GPU, 16 GB of RAM, and an 11th-generation Intel Core i7 processor.

Results

The results confirm that our model can generalize well on the dataset, even when trained on index-transformed images rather than standard RGB inputs. By adjusting the channel coefficients of the best-performing index, CIVE, it is possible to maximize the visual contrast of the leak relative to the background, making it easier for the object detection model to detect. As shown in Table 2, the modified CIVE index achieved the highest performance, surpassing RGB, ExGR, and the original CIVE formulation. The results confirm that the adjusted coefficients in the modified index were able to maximize the visual contrast between the leaks and the background, facilitating the learning process of the YOLO12n.

In contrast, the original CIVE index showed limited performance (0.157 mAP@50), indicating that its default coefficients were not optimal for the optical properties of the underwater environment with blue lighting.

The use of the modified CIVE index enabled the detection model to generalize better on the test set, reducing false negatives and improving the localization of leaks even in visually challenging scenarios. These results confirm the initial hypothesis that adjusting the index coefficients to the specific optical characteristics of the experimental setup would increase leak-background contrast and, consequently, detection accuracy, enabling accurate and computationally efficient detection in contexts where large-scale datasets are unavailable. Furthermore, the approach proved to be compatible with lightweight architectures such as YOLO12n, demonstrating that high-performance results can be achieved without the need for complex or resource-intensive

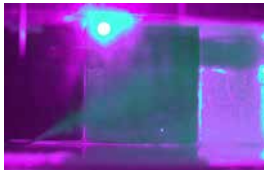
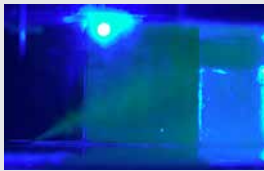
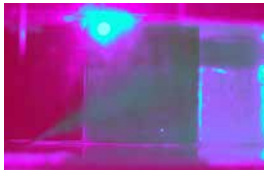

models, which is a key requirement for real-time applications in off-shore operations.

Conclusion

In this study, we propose an approach for detecting underwater liquid leaks using image-based techniques, vegetation indices, and deep learning. To address the limitation of available data, we employed color indices calculated from RGB channels. The YOLO12n model was trained on a custom dataset of fluid leaks captured under external blue lighting, applying post-processing techniques to the CIVE vegetation index to maximize the contrast between the leak and the background. This strategy resulted in a model that outperformed the use of raw RGB images without post-processing, as well as other evaluated indices.

This research highlights the potential of deep learning for leak detection through image processing techniques applied to solving environmental problems.

Table 2. YOLO12n performance using index + G + B channel combinations as input (RGB as baseline).

Input Configuration	mAP@50	mAP@50:95	Image Sample
CIVE (modified, proposed)	0.555	0.278	
RGB (original image)	0.225	0.079	
CIVE (original)	0.157	0.058	
ExGR	0.087	0.017	

For future work, we intend to improve the models and expand the dataset. We will also investigate new coefficients to optimize vegetation indices, aiming to maximize leak contrast. This optimization seeks to enhance algorithm learning and improve evaluation metrics. In addition, we plan to employ quantitative metrics for coefficient determination, replacing the exclusively visual criterion currently used.

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