Leak Detection in Hermetic Compressors using Computer Vision and Artificial Intelligence

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Summary

Detecting leaks in hermetically sealed cooling equipment is crucial for the refrigeration industry, as manufacturing defects may lead to refrigerant loss or even render cooling systems completely inoperable. Currently, in the refrigeration sector, leak verification in hermetic compressors is typically performed through manual human inspections, which can potentially cause worker fatigue and exhaustion. In this working paper, we tackle the problem of automatically detecting manufacturing defects in hermetic compressors using computer vision-based solutions. More specifically, we design an AI-based approach that integrates optical flow algorithms, image processing filtering, and neural networks to detect bubbles when the compressors are submerged in a water tank. By experimentally analyzing the leakage detection problem on preliminary real image compressor videos, our computer system was able to automatically detect failures in damaged compressors in an accurate and efficient way.

1 Introduction

The refrigeration industry has made significant efforts in recent years towards developing new technologies to optimize the performance, durability and reliability of cooling equipment. Among the key components manufactured by this industrial segment, we can cite the hermetic compressor, which has been extensively used in a variety of cooling systems, particularly in household and commercial refrigeration, encompassing air conditioning units as well as refrigerators.

Specially, hermetic compressors refer to refrigeration units that are enclosed within welded steel casings, ensuring a sealed environment while offering enhanced efficiency and reliability. The hermetic seal effectively prevents the infiltration of air and moisture into the compressor, thereby conferring the advantage of immunity against gas and liquid leaks, which is a crucial feature of this type of cooling component.

The commercial applications of hermetic compressors are diverse, prompting the refrigeration industry to address important considerations regarding the component's reliability and durability during the manufacturing process. Concretely, a critical task is to ensure the absence of leaks in hermetic compressors, as manufacturing defects may lead to unwanted refrigerant loss, significantly impacting the efficiency of air conditioning units or refrigeration systems. Furthermore, an unexpected leak can pose risks to human health, given that certain refrigerants emit pollutants.

Therefore, in this collaborative research endeavor with the cooling industry, we focus on detecting manufacturing defects in hermetically sealed compressors. Specifically, we aim to automatically identify cooling compressors with manufacturing failures by designing computer vision-based solutions. In more technical words, this is accomplished by automatically detecting bubbles when the compressors are submerged in a water tank. The formulated approach integrates optical flow algorithms, image processing filtering, and Artificial Intelligence (AI) driven tools to effectively address the leakage detection problem in refrigeration compressors.

2 Problem Description

Founded in 1934 in Tecumseh, Michigan (US), the *Tecumseh Products Company* has been instrumental and revolutionary in transforming the cooling industry. The company notably introduced the pioneering concept of hermetically sealed compressor, in 1937 [12]. Currently, the company produces a wide range of hermetic compressors for both residential and commercial use, as well as a variety of indoor and outdoor condensing units, evaporators, complete refrigeration systems, and components for authorized component replacement services.

Among the refrigeration components produced and manufactured on a large scale by the Tecumseh company, the hermetically sealed compressor plays a fundamental role in the corporation's revenues. As previously mentioned, one of the main advantages of hermetic compressors is their immunity to gas and liquid leaks. As a result, fully sealed compressors are expected to exhibit minimal leakage-related failures, particularly in the welded areas of the casing.

Currently, to ensure the detection of leaks while preventing the distribution of faulty compressors, the company keeps a human operator standing in front of a water tank equipped with moving hooks. The operator inspects the pressurized compressors as they move, carefully examining for any indications of leakage (see Figure 1).

Therefore, in an effort to tackle the issue of detecting components vulnerable to leakage, in this study group we formulate and implement a potential computer vision-based solution to fully automate the leak recognition process in hermetic compressors. Specifically, we apply and integrate optical flow-based approaches, image processing filtering and deep learning-driven strategies to identify signs of leaks in pressurized compressors, by processing video data taken directly from the water tank (see Figure 1).

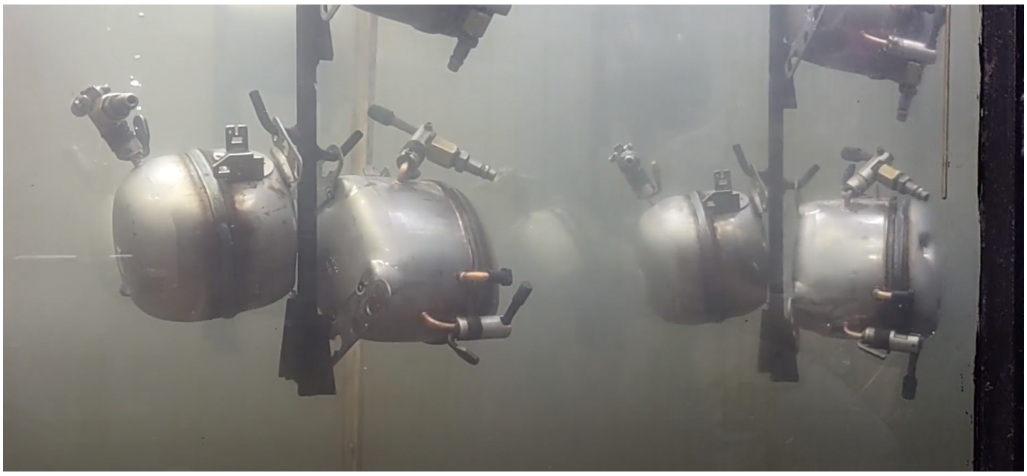

Figure 1. Compressors submerged in a water tank for leak testing.

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3 Methodology

In this section, we describe the main proposals discussed by the working team toward addressing the aforementioned problem. The following approaches were discussed: (i) design a computer vision system based on image processing techniques and artificial intelligence tools; (ii) develop an acoustic detection system based on laboratory experiments and computer simulations. Due to the unavailability of acoustic data from the company for conducting experimental analyzes, the team focused on the proposed solution (i), which aimed to implement a computer vision-based approach capable of accurately segmenting and recognizing leaks in cooling compressors moving in a water tank.

Concerning the implemented computer vision system, we highlight the following goals and methodological steps:

- Design a robust, fully automated computer vision-based solution to segment and identify leaks in hermetic compressors.
- From a digital video camera, detecting which compressors have manufacturing defects by capturing bubbles expelled in the water, hence improving the current inspection protocol of the company that places a worker in charge to manually detect defective compressors moving in water tanks.
- Implement an artificial intelligence-driven system for hermeticity testing, automating the detection task while ensuring cost reduction (i.e., the full system automation).
- Classify the leaks from the defective hermetic compressors by analyzing the frequency and flow characteristics of the bubbles.

3.1 Computer Vision System Development

3.1.1 *Motion Detection and Quantification*

Motion detection is a set of techniques devoted to identifying and quantifying changes in the position of objects relative to the reference frame of the camera that captures the images [10]. These techniques have been widely studied with a focus on security and surveillance, such as controlling the traffic of people, animals or cars in a given location. In general, motion detection algorithms perform image post-processing from a video generated by digital cameras, mapping and tracking objects through time.

The video input can be represented as a time series of two-dimensional images I_i, $i = 1, 2, ..., t$, of dimensions $m \times n$. The basic principle of motion detection is to compare a given frame to the previous one by subtracting the pixels from both images. By applying this approach, static regions, i.e. with small variations of pixels between the frames, will tend to cancel out, while changes in pixels caused by motion will tend to stand out [7].

After detecting several moving objects, the quantification of their motion allows the selection of specific objects or situations of interest. In the problem studied here, for example, there is a constant horizontal movement of the target compressors and, when present, vertical movement of bubbles. As a result, aiming at distinguishing the bubbles from other unrelated elements present in the video, we take the direction and speed of each object as selection criteria. The velocity field of moving objects is obtained by using the concept of optical flow, as described next.

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The application of the optical flow relies on two basic characteristics: (i) the pixels of the same object do not change significantly in intensity between frames, and (ii) neighboring pixels move in a similar way. Given a pixel $p(x, y, t)$ in an initial frame, after moving a distance dx and dy in a time interval dt, the following expression holds:

$$p(x, y, t) = p(x + dx, y + dy, t + dt) = p(x, y, t) + \frac{\partial p}{\partial x}dx + \frac{\partial p}{\partial y}dy + \frac{\partial p}{\partial t}dt, \tag{3.1}$$

where the first equality corresponds to criterion (i), while the second one is related to the first order Taylor series expansion of the pixel p at $t + dt$.

Since the sum of the last three terms in Eq. (3.1) must be equal to zero due to criterion (i), we obtain the following equation:

$$\frac{\partial p}{\partial x}\frac{dx}{dt} + \frac{\partial p}{\partial y}\frac{dy}{dt} + \frac{\partial p}{\partial t} = \frac{\partial p}{\partial x}u + \frac{\partial p}{\partial y}v + \frac{\partial p}{\partial t} = 0, \tag{3.2}$$

where $u = dx/dt$ and $v = dy/dt$ are the velocities of the pixel in the x and y directions, which are unknown. Therefore, we have an under-determined system composed of one equation and two unknowns.

By employing criterion (ii), we can select a patch of 3×3 pixels around $p(x, y, t)$ and, by assuming equal motion between them, the mathematical problem becomes over-determined with nine equations and two unknowns, which can be properly solved via the least squares method. This technique, denoted by the Lucas-Kanade method, allows for the calculation of the velocity vector (u, v) of the moving object, quantitatively characterizing its motion [1].

The above-described steps of motion detection and quantification are implemented by taking the well-established *Open Source Computer Vision* (OpenCV) library, available for free in C++, Python, Java, and Matlab languages. OpenCV is a free software library for computer vision, machine learning and image processing that currently plays an important role in real-time operations [8]. In this work, we take the Python version of OpenCV to run our experimental tests.

3.1.2 *Artificial Intelligence Architecture for Object Detection*

The task of object detection in digital images and videos plays a vital role in many computer vision applications, being indispensable to accomplishing a variety of complex computational tasks such as object tracking, behavior analysis and event detection [2, 9]. In this context, the use of Artificial Intelligence (AI) techniques is becoming increasingly prevalent, enabling more accurate and efficient object segmentation, recognition, and classification [5].

In 2016, the so-called *You Only Look Once* (YOLO) architecture, a deep learning network [11] was published to address the problem of object detection in real-time videos in an automatized and accurate way. Such an architecture allows for object detection in such a way that *bounding boxes* are provided in real-time videos due to the quick image processing performed by the AI-based network. Over the years, the YOLO architecture has undergone recurrent optimization, resulting in different improved versions. In our implementations, the YOLOv5s architecture [4, 3] was taken and tuned to capture moving compressors in the image frames.

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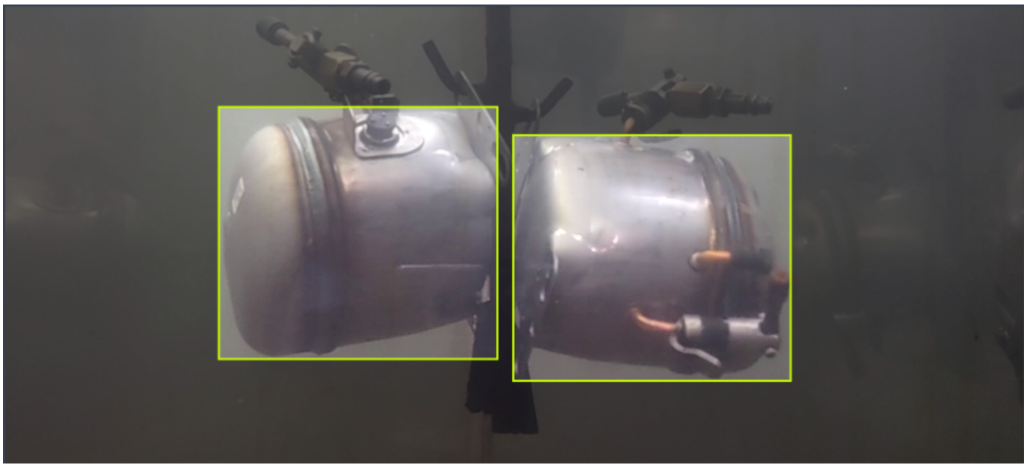

Figure 2. Manually labeled compressor bounding boxes in a video frame.

In order to computationally improve the object detection task as delivered by the YOLOv5 network, a deep reinforcement learning strategy was adopted [6], where the weights of the network already trained for general object detection are used as input for the training of submerged compressor detection. This approach enables faster network training for this particular detection task.

Prior to training our detection model, we manually label a set of compressor images to create a dedicated training dataset for this specific detection application, as shown in Figure 2. In our approach, the goal of compressor detection is to eventually identify the source of the leak. As a consequence, only the region of interest (hull) was labeled.

After labeling a set of trainable images, we train the network to automatically detect these new targeted objects, resulting in a classification model that is able to capture compressors from video data.

Finally, in the last step of our AI-guided framework, we conduct the final stage of the leak detection task by applying image processing filtering and optical flow techniques, as described earlier in Section 3.1.1. Specifically, the leaks are detected by processing the bounding boxes with the targeted compressors as delivered by our classification model.

4 Experimental Results with Real Compressor Images

In this section, we present the main experiments conducted by our working team, which focused on the analysis of a dataset composed of real compressor images provided by the refrigeration company.

Through comprehensive experimental analysis and comparison with ground-truth data recorded in video formats, we discuss insightful findings and compelling results that demonstrate the viability and effectiveness of our computer vision system for real-world compressor image analysis.

4.1 Motion Detection and Optical Flow

Our goal is to develop a computational approach that automatically detects leaks in hermetic compressors. An effective way to accomplish this task is by calculating the number of moving objects from the video frames during a leak. Figure 3 (left) shows an example of a typical scenario induced by a faulty compressor. One may notice that when the compressors are sealed (see Figure 1), the only moving objects detected by the frame difference are the hook base and the compressors. As one can verify in Figure 3, if there is a leak, several small objects, which correspond to bubbles, will appear in the video.

A straightforward way to distinguish frames with faulty compressors from those without is to monitor the total number of moving objects. In Figure 4, we select a time window where three notable leaks occur, and then check the number of objects detected as a function of the frame index. From the visual results, during frame instants in which there are leaking compressors, the quantity of moving objects becomes significantly higher than in the frames with functional compressors.

We also notice from Figure 4 that isolated peaks can occur in periods outside the leak regions. Nevertheless, those fluctuations are likely attributed to camera movements and they are not consistent over time. Thus, in order to avoid the influence of this irregular behavior, one could in principle design a leak detection pipeline based on a smoothed version of the time series as seen in Figure 4. Here, however, we refine our methodology by taking into account the movement direction. The sudden increases in the number of objects are caused by spurious events in the video recording process, and the direction of

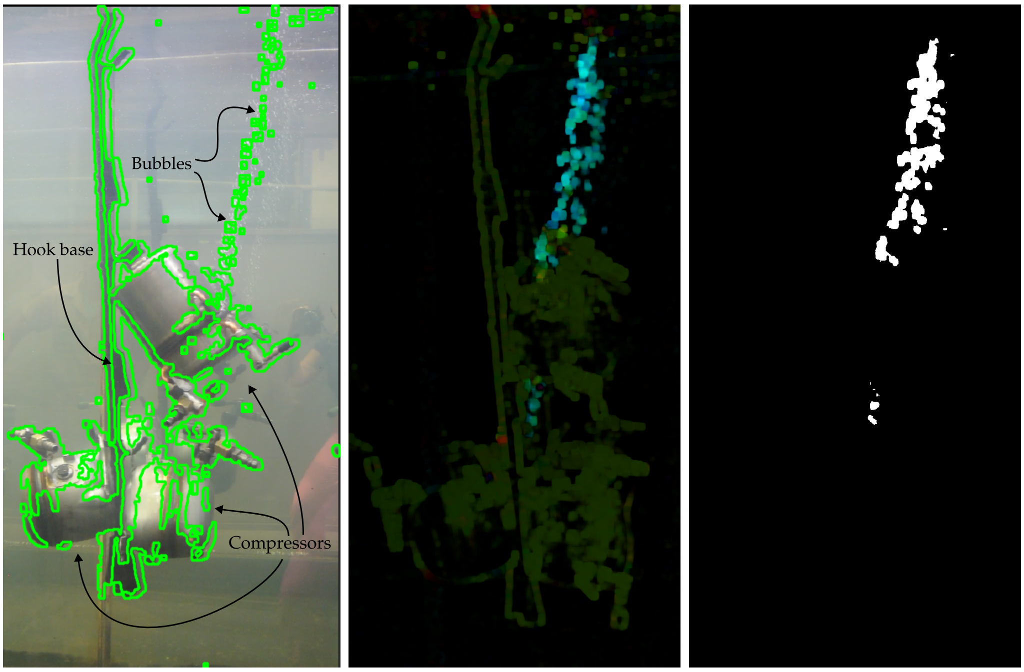

Figure 3. (Left) Motion detection: marked areas (in green) correspond to moving objects in the frame. (Middle) Leak detection using optical flow: light colors indicate objects (bubbles) moving towards the surface. (Right) Leak segmentation after post-processing.

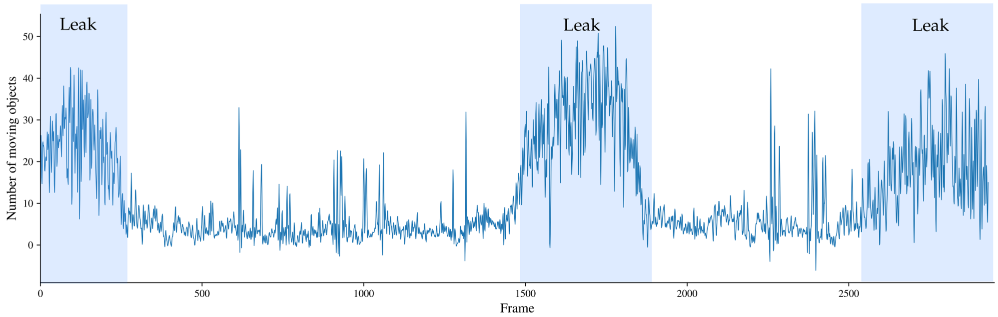

Figure 4. Motion detection and counting of moving objects: peaks correspond to periods with compressor leakage. A high number of moving objects indicate the presence of bubbles. Low counting numbers likely indicate no leakage.

movement of those objects is random. The bubbles caused by leaks, on the other hand, have a very well-defined velocity vector, which always points to the surface of the tank.

In order to detect a leak, it suffices to select only those moving objects that have a specific direction. This can be effectively performed by computing the optical flow of the frames, as described in Sec. 3.1.1. Figure 3 (middle) exemplifies the optical flow implementation, where the highlighted pixels indicate the angle of the movement. Once the direction of the leaking bubbles is identified, we apply an image thresholding technique to get a binary representation of the objects created by faulty compressors (see Figure 3 - right). These results demonstrate the viability of our approach to improving quality control in the manufacturing of hermetic compressors.

4.2 AI-based compressor detection

Aiming at training the YOLOv5s network using the company's available video data, a dataset of 157 images was initially labeled. As part of pre-processing step when annotating the images, they were resized to 624×624 pixels. Additionally, the dataset was augmented through rotation operations. The inclusion of rotated images allows the network to enhance its learning ability in capturing compressors at various positions, thereby increasing the dataset size while improving the detection task. Figure 5 shows a

Figure 5. Different rotations of the same training image.

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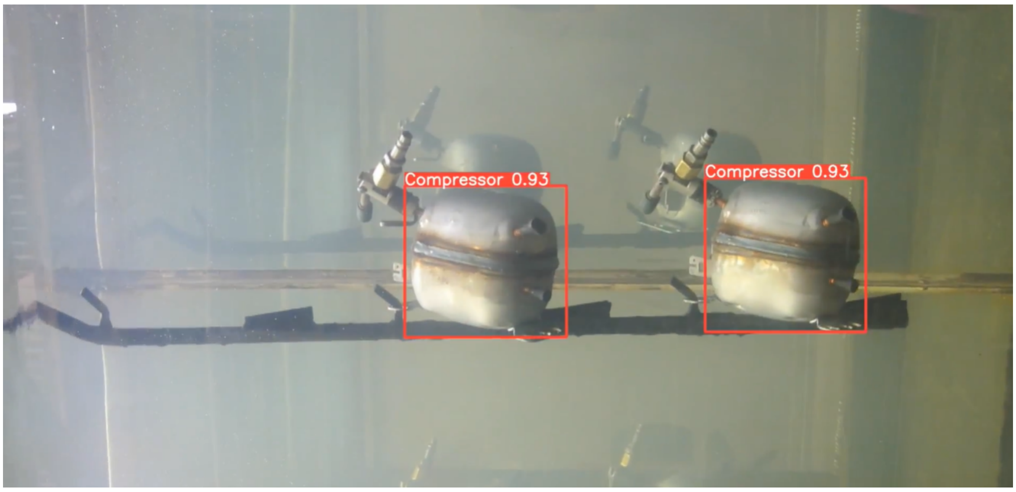

Figure 6. Detection performed on a rotated frame.

few rotated frames after applying the aforementioned step, while Figure 6 illustrates the detection of a rotated frame.

The complete dataset is composed of 373 images, where 325 of them were taken in the training step, 31 for validation, and 17 for the testing stage. During the training stage, the dataset was divided into batches of size 32, and the initial weights for the reinforcement learning process were obtained from the YOLOv5s pre-trained model [6]. Figure 7 shows how the network performs after training for 10 epochs using 157 labeled images (109 for training, 31 for validation, and 17 for testing).

The training process was conducted for a total of 1000 epochs, with an early stop condition implemented after 100 epochs without improvement. The training was successfully completed in 0.498 hours using the NVIDIA TU104GL. In terms of detection accuracy,

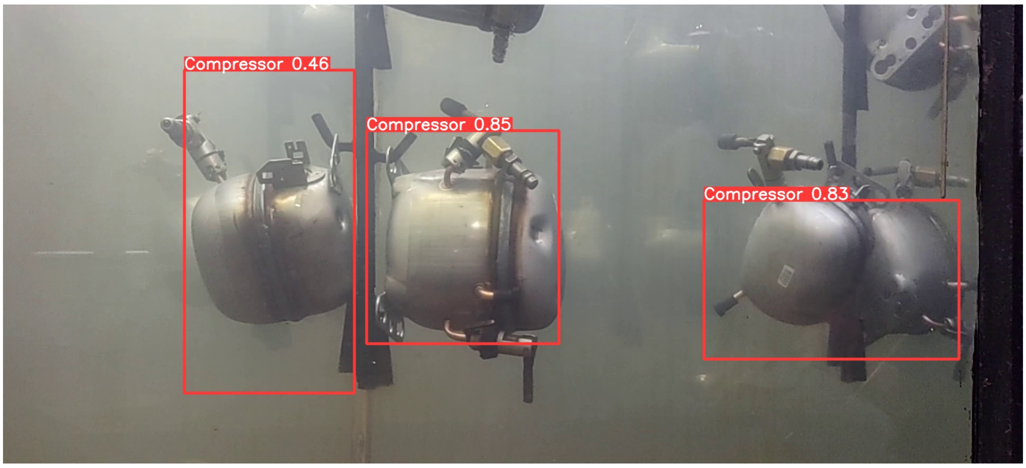

Figure 7. Preliminary results when training the YOLOv5s AI-based network with only a few epochs.

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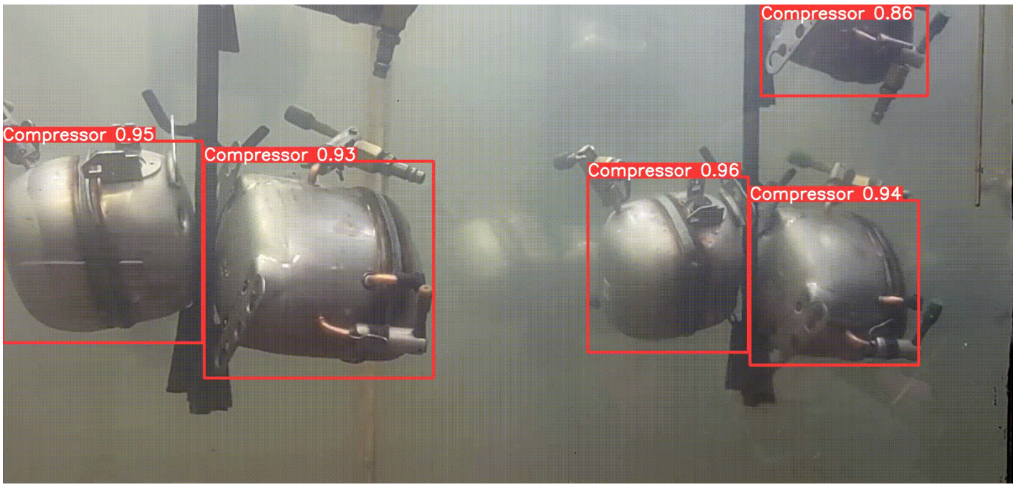

Figure 8. Definitive output after the detection network is fully trained.

the definitive trained model achieved an overall accuracy of over 94% in capturing the target compressors. Figure 8 illustrates a video frame obtained after the entire training process has been completed.

5 Conclusion

In this collaborative working paper with the cooling industry, we tackled the problem of detecting manufacturing defects in hermetically sealed compressors using fully automated computer vision-based solutions. By integrating optical flow algorithms, image processing filtering, and artificial intelligence driven tools, the implemented computer vision system was capable of automatically identifying bubbles expelled when the compressors are submerged in a water tank equipped with a moving hook.

The experimental analysis carried out on a real dataset comprising both sealed and faulty compressors, as provided by the refrigeration company, has provided valuable insights and compelling results, confirming the effectiveness of our computer vision system for dealing with compressor images in real-world scenarios. By automating the detection process, we can reduce reliance on manual human inspections, mitigate worker fatigue, and enhance overall efficiency in the refrigeration industry. Our findings contribute to advancements in leakage detection in refrigeration compressors, providing a foundation for future research in this area.

As a future direction, conducting studies and experimental tests utilizing acoustic-based solutions, such as the use of a hydrophone, could be a promising approach. Additionally, other deep learning networks and tuning strategies could be considered for accurate classification of bubble size, flow rate, and other relevant data. Finally, the generation of massive training data from controlled and appropriate conditions in a laboratory could also advance the recognition of leak patterns.

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References

[1] Florian Becker, Stefania Petrab, and Christoph Schnörr. *Optical Flow*, pages 1–54. Springer New York, 2020.

[2] Jun Deng, Xiaojing Xuan, Weifeng Wang, Zhao Li, Hanwen Yao, and Zhiqiang Wang. A review of research on object detection based on deep learning. *Journal of Physics: Conference Series*, 1684(1):012028, nov 2020.

[3] T. Diwan, G. Anirudh, and J.V. Tembhurne. Object detection using yolo: challenges, architectural successors, datasets and applications. *Multimedia Tools and Applications*, 82(23):9243–9275, 2023.

[4] Glenn Jocher, Ayush Chaurasia, Alex Stoken, et al. ultralytics/yolov5: v7.0 - YOLOv5 SOTA Realtime Instance Segmentation, November 2022.

[5] Ravpreet Kaur and Sarbjeet Singh. A comprehensive review of object detection with deep learning. *Digital Signal Processing*, 132:103812, 2023.

[6] Ngan Le, Vidhiwar Singh Rathour, Kashu Yamazaki, Khoa Luu, and Marios Savvides. Deep reinforcement learning in computer vision: A comprehensive survey. *arXiv preprint arXiv:2108.11510*, Aug 2021.

[7] Da Li, Bodong Liang, and Weigang Zhang. Real-time moving vehicle detection, tracking, and counting system implemented with OpenCV. In *IEEE International Conference on Information Science and Technology*, pages 631–634. IEEE, 2014.

[8] Shubham Mishra, Mrs Versha Verma, Nikhat Akhtar, Shivam Chaturvedi, and Yusuf Perwej. An intelligent motion detection using OpenCV. *International Journal of Scientific Research in Science, Engineering and Technology*, pages 2395–1990, 2022.

[9] Rogério G. Negri, Andréa E. O. Luz, Alejandro C. Frery, and Wallace Casaca. Mapping burned areas with multitemporal–multispectral data and probabilistic unsupervised learning. *Remote Sensing*, 14(21):5413, Oct 2022.

[10] Suraiya Parveen and Javeria Shah. A motion detection system in python and OpenCV. In *IEEE International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, pages 1378–1382. IEEE, 2021.

[11] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi. You only look once: Unified, real-time object detection. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 779–788. IEEE Computer Society, 2016.

[12] Tecumseh Products Company. Company history, February 18, 2023.