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Detecting Underwater Concrete Cracks with Machine Learning: A Clear Vision of a Murky Problem

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Abstract: This paper presents the development of an underwater crack detection system for structural integrity assessment of submerged structures, such as offshore oil and gas installations, underwater pipelines, underwater foundations for bridges, dams, etc. Our focus is on the use of machine-learning-based approaches. First, a detailed literature review of the state of the current methods for underwater surface crack detection is presented, highlighting challenges and opportunities. An overview of the image augmentation approach for the creation of underwater optical effects is also presented. Experimental results using a standard network-based machine learning approach, which is used for surface crack detection in onshore environments, are presented. A series of test cases is presented in which existing networks' performance is improved using augmented images for underwater conditions. The effectiveness and accuracy of the proposed approach in detecting cracks in underwater concrete structures are demonstrated. The proposed approach has the potential to improve the safety and reliability of underwater structures and prevent catastrophic failures.

Keywords: underwater; crack detection; machine learning; transfer learning; augmentation; non-destructive testing; safety; reliability

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1. Introduction

Underwater concrete structures serve various important purposes in different areas, including infrastructure projects, erosion and storm protection, support for offshore energy projects, and the creation of habitats for marine life. These structures are designed to provide stability, durability, and the ability to withstand harsh underwater environments. They play a crucial role in supporting infrastructure development while also protecting the environment and marine ecosystems. Ensuring the structural integrity of underwater concrete structures is of the utmost importance for preventing catastrophic failures. The underwater environment poses unique challenges to the integrity of these structures, such as saltwater corrosion and the impact of waves, which can lead to cracks and other types of damage. It is vital to identify and monitor fractures in underwater concrete constructions to identify potential weaknesses and take corrective measures in a timely manner.

However, it is a challenging endeavor to identify and monitor fractures in underwater concrete constructions due to several factors. Limited visibility, difficult access, and harsh conditions make it difficult to visually inspect these structures. Therefore, reliable and efficient methods are needed to detect and monitor cracks in underwater environments. Some of the most frequently used methods for fracture identification and monitoring in underwater concrete structures are:

- Visual inspections by divers: Specially trained divers can perform visual inspections of the structures to identify visible cracks or signs of damage. However, this method is limited by the accessibility of the structure and the diver's ability to navigate and inspect the entire surface. Such inspections are also known for high risk for the divers involved in carrying out such inspections.

- Non-destructive testing techniques: Techniques such as ultrasonic testing and acoustic emission monitoring may be used to evaluate the interior condition of a concrete structure and detect cracks or other flaws. These methods rely on the analysis of sound waves or emitted signals to identify potential issues. However, they require specialized equipment and expertise to perform accurately. The time required to acquire and process data is long. Often, the cost of such data acquisition is very high as well.
- Advanced technologies: Underwater drones and robots equipped with cameras and sensors are emerging as valuable tools for crack detection and monitoring. These autonomous or remotely operated devices can access hard-to-reach areas, capture high-resolution images or videos, and collect data on the condition of the structures. This technology offers improved accessibility and accuracy in crack detection. The technique presented in this paper is an addition to this type of technology for underwater inspections.

In the present time, the amount of underwater infrastructure has increased manyfold, including internet cables, electric cables linked to offshore wind mills, and oil and gas pipelines, among other important infrastructure. Implementing reliable methods for detecting and monitoring cracks in underwater concrete structures is crucial for ensuring their long-term durability and safety. While significant research has been conducted on crack detection systems for onshore and above-water structures [1,2], less attention has been given to underwater crack detection. The work presented in this paper focuses specifically on addressing this gap and developing effective crack detection methods for underwater concrete structures. By improving our ability to detect and monitor cracks in underwater concrete structures, we can identify issues early, implement appropriate repairs or maintenance, and ensure the continued functionality and safety of these vital underwater assets.

The paper is structured as follows: An overview of different techniques used in underwater concrete crack detection is presented in Section 2. Challenges in underwater concrete crack detection and mitigation methods are discussed in Section 3. Section 4 presents an overview of the data set used in this paper to demonstrate use of a machine-learning-based approach for underwater crack detection. A machine-learning-based underwater crack detection system and a series of test cases are presented in Section 5. Conclusions follows in Section 6.

2. An Overview of the Techniques Used for Underwater Concrete Crack Detection

2.1. Visual Inspection: Basic Method for Detecting Cracks in Underwater Concrete, Limited by Water Clarity and Visibility

By quantifying the likelihood distribution of sea surface slopes, numerical approaches have enabled researchers to investigate both the refraction and reflection of light from the sky and the sun via roughened sea surfaces. In one study, the researchers explored various optical phenomena, such as the refracted sun's glitter, the brightness and reflectivity of an uneven sea surface owing to sky light, and the reflection of a harsh sea surface from direct sunlight [3]. While research on cracks in underwater surfaces is limited, most studies focus on the effects of water on various chemicals, their resistance to the environment, or their impact on the environment [4–6].

Researchers have studied shade on underwater optical radiometers employing Monte Carlo computations of a light field with both the presence and absence of the sensors [7]. Optical sensors from space have been used to observe surface water, and various techniques have been developed to eliminate cloud or terrain shadows [8–12]. Additionally, flash photography directed vertically downward toward the water surface has been used to interpret wave slopes. Researchers have studied various optical effects of water, including optical absorption, temperature and humidity effects, dissolved organic materials, biological vegetation interaction, pressure effects, and optical propagation in turbulent water [13–20].

2.2. Acoustic Methods: Use of Sound Waves to Detect Cracks, Including Impact-Echo, Impulse Response, and Ultrasonic Methods: Fluorosensor

In [21], the authors describe how optically and near-infrared wavelengths may be used to detect water depth and substrate type as two key factors in river physical habitats. The approach provided in [22] was used to remotely track chlorophyll content in fresh waterways and was shown to be strongly associated with real-world data, allowing for the detection of changes in surface water optical attenuation.

Another research study investigated the association between acoustic emission cumulative energy and decreased cycling reversal loads in submerged concrete columns [23]. Ultrasonic surface waves were used to detect cracks in underwater concrete beams, with a root mean square deviation damage index used to analyze the wave data [24]. A method for assessing the concrete dams' blast resistance by investigating the induced vibration and crack penetration depth and use of a crack control agent to prevent failure of concrete structures was presented in [25,26].

2.3. Electrical Methods: Use of Electrical Resistance or Capacitance to Detect Cracks, etc.

The coordination and electrostatic effects of water's optical absorption were resolved through computational analysis in [13]. A Monte Carlo calculation procedure was used in a computer simulation study to investigate the impact of the photon incidence angle on the relationship between natural waters' visible and inherent optical characteristics in [27]. An approach that centered on water's inherent optical properties to fix water angular effects leaving brilliance was presented in [28].

2.4. Magnetic Methods: Use of Magnetic Fields to Detect Cracks, Including the Magnetic Flux Leakage Method

Ground-penetrating radar, or GPR, is a high-resolution, non-destructive technology for detecting hidden things via a high-frequency electromagnetic pulse. It has been widely used in a variety of fields including engineering/geologic research and underground historical research to identify scour holes around bridge piers, etc. It has also been used to assess the structural condition of underwater hydraulic structures [29].

2.5. Deep-Learning-Based Methods: Image Analysis of Cracks Using Deep Learning

Recently, neural networks have been increasingly applied to the quality of surface water estimation, utilizing combined optical and microwave data. These networks excel in approximating nonlinear transfer functions and, as such, research is involved for extracting data from water sample locations and analyzing digital data through various transformations [30]. In [31], A application for Windows was created to simulate and evaluate optical observations in aquatic settings.

Surface water detection is important for understanding flood hazards and potential damage to infrastructure and ecosystems. In [32,33] the applications of satellite remote sensing and its limitations in detecting and monitoring surface water, mapping, and parameter estimation were discussed.

An unsupervised method for identifying fractures in underwater concrete structures was offered in [34]. For eliminating outliers, the approach depends on local feature clustering utilizing K-medians on Haralick texture characteristics with a dual Gaussian distribution. Detecting and classifying cracks in underwater dam structures based on sonar images is a difficult task due to the complexity of underwater environments and the random and diverse nature of cracks, as well as the low resolution of sonar images. In [35], a clustering analysis was performed on a 3D feature space to obtain crack fragments, which were then connected using an improved tensor voting method. Ref. [36] presented an alternate technique for identifying underwater dam breaches in sonar imagery. The cracked block tree (BT) approach comprises pre-processing low-resolution sonar pictures, breaking them down into pieces for grouping analysis, and combining the crack segments with dynamic fragments of fractures based on tensor voting. In [37], a two-phase system was proposed for robust crack detection in concrete and pipelines inspections using remotely operated vehicles. Ref. [38] proposed a two-step approach for automatically identifying concrete fractures in aquatic situations. In the first step, the images were pre-processed through illumination balancing and image smoothing, and in the second step, a convolutional neural network (CNN) was used for crack detection.

In [39], a novel algorithm was proposed that generated a 3D spatial surface from the intensity values of a 2D image. The cracks were identified as "ditches" in the 3D surface, and their characteristics were analyzed using space curvatures. A BP neural network was then used to identify the crack objects. In [40], an artificial colony of bees algorithm-based edge extraction methodology was proposed. To improve the weak-object border gray contrast, an adaptive enhancement approach was applied, and a method of optimization using border direction information was presented to improve the edge extraction efficacy. Ref. [41] presented the establishment of a free aquatic light and turbid images repository (ULTIR) to assess the efficacy of image-based approaches for underwater structural evaluation.

In [42], an automatic crack detection method using image processing was proposed. The approach created an augmented picture based on turbidity meter absorbance and eliminated the background component. Crack detection was performed using a decision tree learning algorithm. Ref. [43] presented a unique automated dam fracture detection technique that utilized local–global clustering analysis. Using photographs, the system can precisely and rapidly detect faults on dam surfaces, decreasing human subjectivity.

In [44], a Tactile Imaging System for Underwater Inspection (TISUE) was conceived, prototyped, and tested. The device combined an elastomer-enabled contact-based optic sensor with specially designed artificial illumination to provide high-resolution and high-quality pictures of the structural damage to the surface in a turbid water environment. Finally, the paper [45] introduced the UIS-1 underwater inspection system, comprising a proprietary underwater robot and a unique quantitative analysis approach. The technology was tested in the field at the dam in Sichuan, China, and its efficacy was compared to that of other approaches. The suggested picture technique detected the coarse aggregate exposed automatically using SLIC super pixels and SVM machine learning, and the total exposure ratio was derived to assess the degree of abrasion.

2.6. Other Methods: Including the Use of Fiber-Optic Sensors, Thermal Imaging, and X-ray Imaging

Rendering water is a key component in creating natural scenes. In [46,47], we offered a method for creating accurate underwater optical effects using graphics hardware utilizing a Z-buffer, a stencil buffer, and an accumulation buffer. Additionally, ref. [48] provided a strategy for evaluating the statistical distribution of water's level slopes using flash photography. Researchers introduced a temperature tracer approach for fracture identification in sub-sea concrete structures based on heat transport theory in [49–51]. A method for controlling concrete cracking in underwater marine structures using basalt fiber was presented in [6].

The study presented in [52] developed a structural health monitoring tool that considered the reciprocal relationships and priority weights of different structural distresses to assess underwater structures. Cracking and collapse behaviors of an undersea shield tunnel's segmental liner construction exposed to a wrecked high-speed train collision were explored in [53]. In [54], researchers looked at the chaotic actions of arched concrete barriers subjected to underwater explosions. In addition, a system using a single camera deployed in a vehicle or robot was proposed in [55] to process a sequence of images and estimate crack dimensions.

Due to uneven lighting and considerable noise issues, detecting and classifying underwater dam breaches is difficult, and only a few approaches are adequate for this purpose. One study [56] presented a dodging algorithm to eliminate uneven illumination, based on an investigation of the statistical aspects of dam crack pictures, employing the regional features of block images and the global features of related domains. In [57], a simpler approach for estimating the wear life of fractured concrete below water was developed, utilizing a changed design code that took into account the crack's reduction in stress amplitude. Ref. [58] studied crack identification and categorization strategies based on crack kinds and then implemented Otsu's base thresholds method for crack detection, which was then utilized to construct the suggested crack detection system.

3. Navigating Challenges Related to Underwater Concrete Crack Detection Using Machine Learning

Working in underwater environments presents unique challenges that require specialized equipment and procedures for inspections. Underwater inspections require specialized diving equipment, including wet suits, diving masks, and tanks for air supply. Divers must be trained in specialized diving techniques, including decompression procedures and safety protocols. Additionally, specialized inspection equipment is necessary, such as underwater cameras, sonar devices, and non-destructive testing equipment.

One of the most significant difficulties in inspecting underwater concrete structures is detecting cracks. Underwater conditions, such as poor visibility, water pressure, and limited access, make it challenging to detect cracks. Visual inspections by divers are often necessary, but they can be time-consuming, expensive, and potentially hazardous. Advanced techniques such as ultrasonic testing, acoustic emission monitoring, and digital radiography are also used to detect cracks in underwater concrete structures.

Optical effects can also impact the quality of underwater images captured by unmanned aerial vehicles (UAVs) used for inspections. Optical effects such as refraction, reflection, and attenuation can distort images and impact the accuracy of inspections. To mitigate the impact of these optical effects, UAVs used for underwater inspections must be equipped with specialized cameras and sensors and operated by trained professionals who can account for these optical effects during inspections. Overall, working in underwater environments requires specialized equipment, procedures, and skills to overcome the unique challenges presented by the underwater environment.

Underwater concrete structures are critical components of many marine-based infrastructures, such as bridges, piers, and offshore oil platforms. Over time, these structures can develop cracks due to various factors, such as corrosion, water pressure, and natural wear and tear. Detecting and monitoring these cracks is essential for ensuring the safety and longevity of the structure. Visual inspection and dye penetrant testing are the traditional methods for crack detection, but they are time-consuming, expensive, and not always accurate. It has already been demonstrated by the works presented in [1,59] that machine learning approaches offer a very promising solution for detecting cracks in underwater concrete structures.

One approach to crack detection using machine learning is image processing of underwater concrete surfaces. Images of the concrete surface can be captured by underwater cameras and analyzed using machine learning algorithms to detect the presence of cracks. The first step in this approach is to capture high-quality images of the concrete surface. The images must be clear, well-lit, and taken at a distance close to the concrete surface. Once the images are captured, they are processed using image processing techniques such as edge detection, thresholding, and morphological operations. These techniques allow the machine learning algorithm to identify cracks in the images accurately.

Next, the images are fed into the machine learning algorithm for training. The algorithm is trained using a dataset of images with and without cracks. The algorithm learns to recognize the patterns in the images that indicate the presence of cracks. The dataset can be augmented to improve the algorithm's accuracy and generalizability.

Once the algorithm is trained, it can be used to detect cracks in new images of underwater concrete surfaces. The algorithm can be deployed on a computer or embedded in a camera system to perform real-time crack detection.

In conclusion, machine learning approaches based on image processing are a promising solution for crack detection in underwater concrete structures. With their high accuracy and efficiency, they offer a reliable way to detect and monitor cracks in this critical infrastructure.

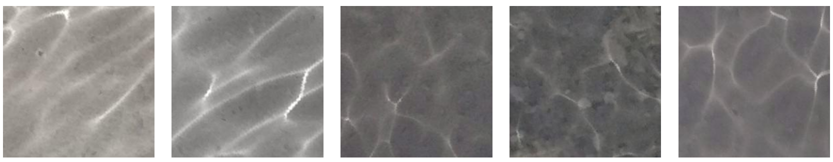
In the next section, we demonstrate the application of deep learning networks for identification of surface cracks in underwater structures. For this purpose, we use AlexNet and SqueezeNet through a transfer learning approach on a large dataset of augmented images. The dataset is generated such that it capture challenges associated with underwater effects.

4. Augmentation of the Concrete Cracks Dataset

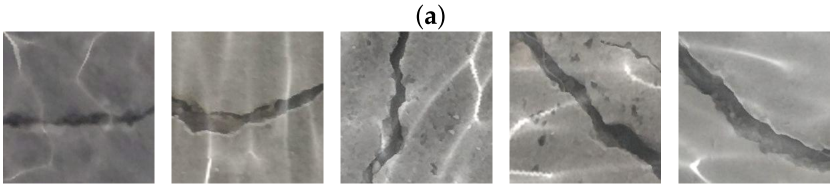
The impact of light on propagation events varies based on seabed topography and streamer depth. By inputting these variables into an underwater wave propagation model, we can anticipate the locations where optical effects will affect the underwater visuals. Wave models are increasingly employed to study and forecast surf conditions in different coastal areas. These models can be developed using wave action or motion systems, which are also known as phase averaging or phase resolving models. The latest generation of phase average models is commonly used in various applications, including commercial tools for flow simulation and wave modeling in advanced professional engineering [59]. In this paper, we have used the model presented in [59] to generate the 3D wave geometry for image augmentation based on the JONSWAP spectrum, which has been proven to be more suitable for a fetch-limited sea with increasing waves [60].

In this study, it is important to have realistic images of underwater concrete structures, so the technique for rendering illumination effects is presented in [59]. First, it is assumed that the surface of the water is level, and the sun's refraction vector is detected. Then, the texture of the surface is developed, representing underwater depth. Finally, the perspective of the scene chosen is that of the human eye. This method was developed with the Blender program [59].

The test of the deep learning method was performed using concrete crack images with and without underwater optical effects. The method used for the generation of underwater optical effects was presented in [59]. The collection contains 40,000 photos of surfaces with and without concrete fractures (20,000 with cracks—"Positive" and 20,000 without cracks—"Negative") from Ozgenel's released dataset, which was used for the test [61]. Optical water illusion effects were generated using the technique depicted in [59], and various modifications (random rotation, zoom, height, width) and different blending techniques were employed for dataset augmentation. For the image classification, 40,000 distinct optical underwater effects were generated and applied to the whole dataset of images with and without cracks; see Figure 1. The technique of image augmentation is presented in detail in [59].



(**a**)



(**b**)

Figure 1. Example of the augmented dataset. Concrete images without cracks and with underwater optical effects are depicted in panel (**a**). Concrete images with cracks and with underwater optical effects are depicted in panel (**b**).

Machine learning methods used for image classification are presented in the next section.

5. Underwater Concrete Crack Detection Using Machine Learning Approaches

Cracks in underwater concrete structures can significantly impact their structural integrity and longevity. As described in the sections above, the traditional methods for detecting cracks in underwater structures are often time-consuming, costly, and require skilled operators. In recent years, machine learning approaches have shown promise for detecting cracks in underwater structures quickly and accurately in onshore environmental conditions [1,2]. In this section, we explore the potential of using machine-learning-based approaches to identify surface cracks on concrete structures in underwater conditions. The concrete cracks in underwater environments are impacted by illumination and presence of marine life, which makes the problem harder to solve compared to surface crack detection in onshore or above-water environments. Two tests are conducted: First, a test involving the standard machine learning network Alexnet [2], trained on surface crack detection for onshore environments described in [1], is used to identify underwater cracks. Next, a test involving an improved version of the network presented in [1], where the network is further trained using augmented underwater images database prepared in [59], is used. The two test cases and their results are presented next.

5.1. Transfer Learning and Use of a Pre-Trained Network

The machine learning approach employed in this paper utilizes transfer learning for training, testing, and validation purposes. This approach is chosen for several reasons. Firstly, it enables the evaluation of various well-established deep learning networks. Moreover, transfer learning saves time by eliminating the need to develop a network from scratch, which can be a challenging task requiring expertise in network design. Furthermore, implementing the transfer learning approach is straightforward and facilitates faster simulation, leading to improved sensitivity within a relatively short time-frame for real-world applications.

The underlying concept of transfer learning involves leveraging a pre-trained network's knowledge and applying it to a similar task by training or exposing it to an additional set of parameters. In the context of this paper, which focuses on image classification, there are several existing pre-trained image classification networks such as SqueezeNet and AlexNet. These networks have been trained to classify a wide range of images, surpassing 1000 categories. Therefore, it is possible to select one of these networks and retrain it for a new classification task. This retraining process involves adjusting some network parameters to classify a fresh set of images. Fine-tuning the parameters of a pre-trained network is considerably faster and easier compared to building a network from scratch. The paper follows this precise approach; for more detailed information on creating transfer learning networks, please refer to [62]. Although numerous pre-trained networks exist that can be used for comparison, in this work, we have kept the focus on using AlexNet and SqueezeNet for analyzing our test cases. The choice of these two networks is dictated by comparison of speed vs. accuracy, as can be seen in Figure 2. AlexNet and SqueezeNet offer the two most reliable and reasonably accurate networks with very high efficiency for prototyping the algorithms. Since the aim of this paper is a prototype and not commercial development, we use these two networks for the following presented cases.

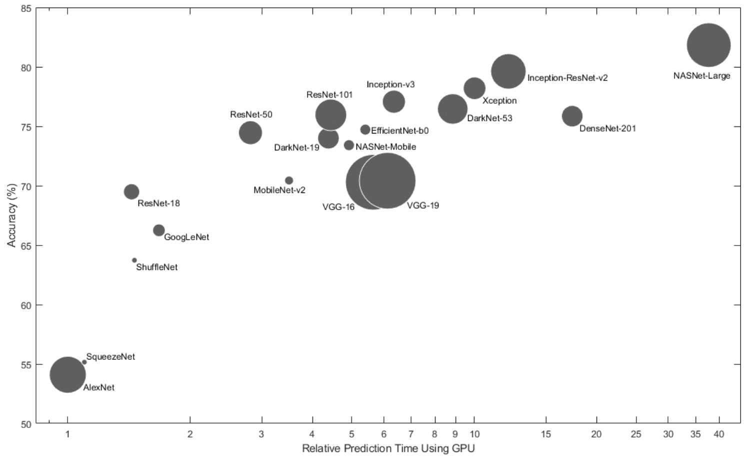


Figure 2. The comparison of speed versus the prediction accuracy of various classification neural networks. Source—www.mathworks.com.

5.2. Test Cases—Review of Performance of Existing Networks on Concrete Images with and without Cracks and Underwater Effects

Detecting cracks on underwater surfaces poses a significant challenge, and conventional image detection networks cannot be directly applied to this problem. To demonstrate the limitations of currently available networks, we conducted a series of tests using a concrete crack dataset, as outlined in our published papers [1,2]. The methodology is based on transfer learning, which is described in detail in [62]. Our evaluation comprised two tests: the first involved training a network to distinguish between crack and non-crack surfaces, while the second tested the same network's ability to detect cracks under conditions of underwater illumination (see Figures 3 and 4 for sample images used in both tests). To conduct our study, we employed two distinct image datasets:

1. Concrete crack images dataset. An example of this dataset is shown in Figure 3.

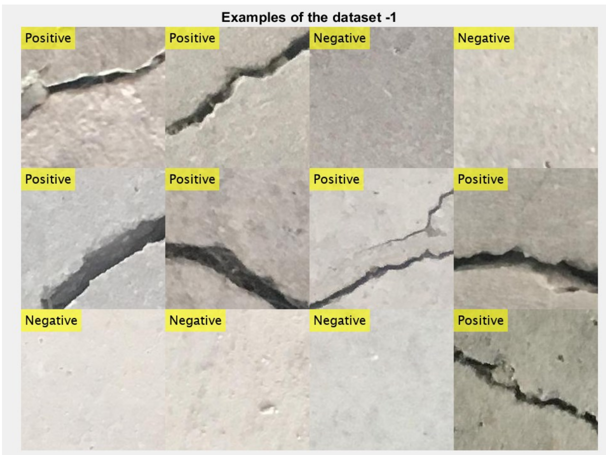


Figure 3. Concrete crack images dataset example.

2. Underwater crack images dataset. An example of this dataset is shown in Figure 4.

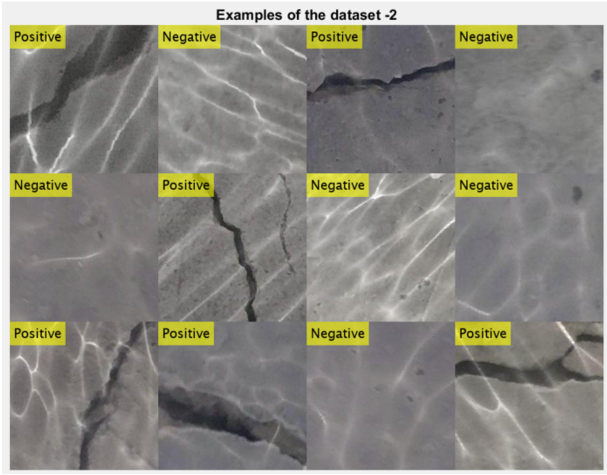


Figure 4. Underwater crack images dataset example.

5.3. Test Case 1: Testing the Trained Network on Identifying Cracks within Non-Crack Surfaces and Using the Same Network to Test Underwater Images

In this case, we used a trained network [1] for identification of cracks within non-crack surfaces in various outdoor settings. The Case 1 characteristics and techniques are as follows:

- Training was conducted on the concrete crack images dataset;
- Testing was conducted on the underwater crack images dataset;
- For case investigation, we used convolutional neural network (CNN) architecture AlexNet and SqueezeNet.

For the investigation in Case 1, we used different training data, testing data, and validation data parameters, which are shown along with the accuracy of the network in Table 1. It can be seen from the results that network accuracy in most cases is above 99%. Two different networks trained using transfer learning approaches described in [1] were used, namely AlexNet and SqueezeNet. Based on Table 1, we can see that using the AlexNet architecture, we obtain the best results when we use these parameters: TrainingData = 0.3; TestingData = 0.3; ValidationData = 0.3.

The results of this case are presented in Figures 5 and 6. It can be seen from these results that, when the network is trained on identifying cracks in surfaces that are in outdoor settings, it works well, with 99.3% accuracy, but the performance of the same network in identifying cracks in underwater images is rather poor, close to 91.6% accuracy only. The poor accuracy is because the network is not trained with underwater images and it found it difficult to identify true cracks, resulting in false positives that reduced the accuracy of the method. The training progress plots, along with training parameters for the case with training, testing, and validation data = 30%, are presented in Figures 7 and 8 for SqueezeNet and AlexNet, respectively. Figures 7 and 8 shows the network training performance. Figure 7 shows the training progress plot for SqueezeNet with training, testing, and validation using 30% of the data for each. Similarly, Figure 8 shows the training progress plot for AlexNet with training, testing, and validation using 30% of the data for each.

Table 1. SqueezeNet and AlexNet results with different training and testing parameters.

Index	Parameters Used for Training Network	Overall Accuracy for Concrete Crack Dataset	Overall Accuracy for Underwater Crack Dataset	Validation Accuracy	Training Time	Epoch	Maximum Iterations	Iterations per Epoch	Frequency	Learning Rate
SqueezeNet										
1.	Training—0.1, Testing—0.1, Validation—0.1	99.2%	84%	97.78%	54 min 29 s	6	186	31	30 iterations	0.001
2.	Training—0.15, Testing—0.15, Validation—0.1	98%	70%	97.80%	87 min 23 s	6	276	46	30 iterations	0.001
3.	Training—0.3, Testing—0.3, Validation—0.3	99.3%	61%	99.17%	104 min 13 s	6	558	93	30 iterations	0.001
AlexNet										
1.	Training—0.1, Testing—0.1, Validation—0.1	99.5%	79%	99.75%	39 min 47 s	6	186	31	30 iterations	0.001
2.	Training—0.15, Testing—0.15, Validation—0.1	99.7%	87%	99.72%	56 min 19 s	6	276	46	30 iterations	0.001
3.	Training—0.3, Testing—0.3, Validation—0.3	99.7%	92%	99.83%	115 min 32 s	6	558	93	30 iterations	0.001

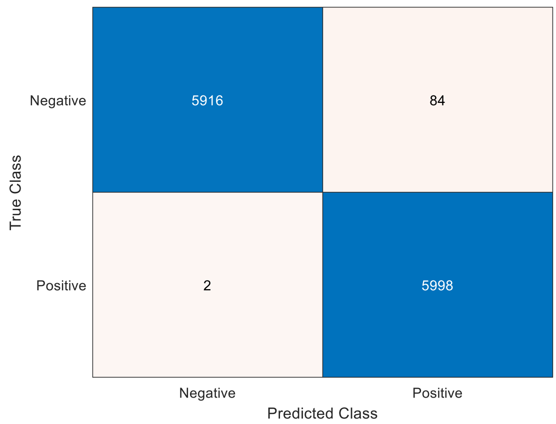


Figure 5. Confusion matrix with concrete crack images dataset (overall accuracy = 99.3%).

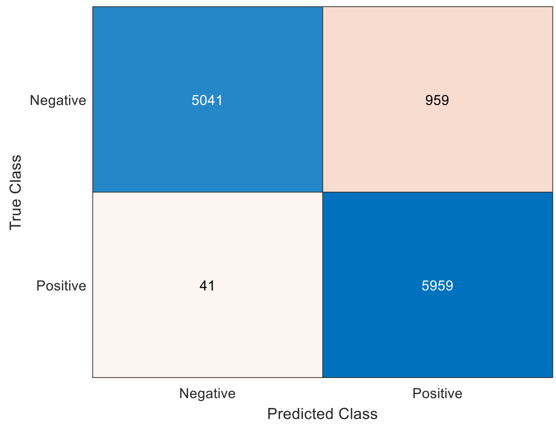


Figure 6. Confusion matrix with underwater crack images dataset (overall accuracy = 91.6%).

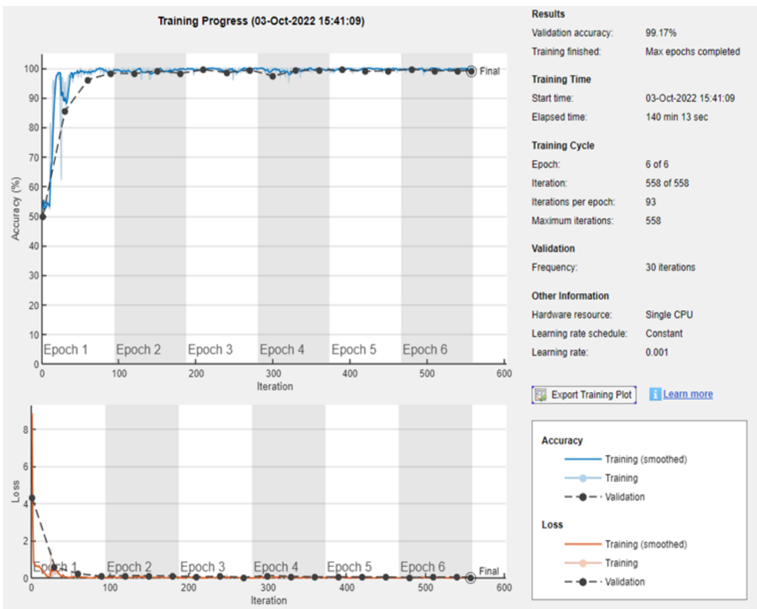


Figure 7. Training progress plots and training parameters for Case 3, using SqueezeNet, with training (30%), testing (30%), and validation data 30% of the total data set. Thus, it uses 90% of the total data.

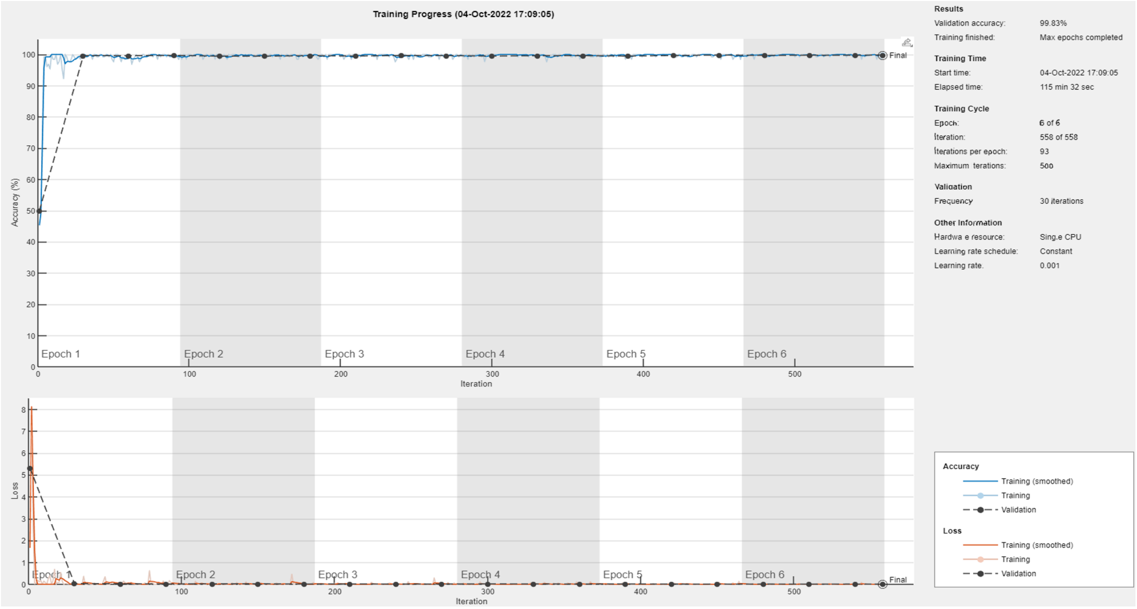


Figure 8. Training progress plots and training parameters for Case 3 using AlexNet, with training (30% data), testing (30% data), and validation data (30%) using 90% of the total data.

5.4. Test Case 2: Testing a Network Trained to Identify Cracks within Non-Crack Surfaces on Identifying Cracks in Underwater Images

In this case, we used the trained network used in Case 1 with additional images, which were augmented to take into account underwater effects, e.g., illumination, shades, color, etc. The trained network was then used for identification of cracks within non-crack surfaces in various outdoor settings in order to identify cracks on underwater images with illumination effects. The Case 2 characteristics and techniques are as follows:

- Training was conducted on the underwater crack images dataset;
- Testing was conducted on the underwater crack images dataset;
- For case investigation, we used convolutional neural network (CNN) architecture AlexNet and SqueezeNet.

For the Case 2 investigation, we used different training data, testing data, and validation data parameters, which are shown in the final Case 2 investigation results table (Table 2). Based on Table 2, we can see that using the AlexNet architecture give us the best results when we use these parameters: TrainingData = 0.3; TestingData = 0.3; ValidationData = 0.3. The results of this case show that, with additional augmented images of underwater effects, the network accuracy is improved to above 99%. The training progress plots along with training parameters for the case with training, testing, and validation data = 30%, as presented in Figure 9. The results of this case are presented in Figure 10.

The two test cases presented here demonstrate that it is possible to improve the performance of existing networks by training them using augmented images such that the network will become able to identifying surface cracks in onshore as well as offshore underwater conditions. Network accuracy could be further improved through parameter optimization and an even better or richer database of augmented images.

Table 2. SqueezeNet and AlexNet results on different training and testing parameters.

Index	Parameters Used for Training Network	Overall Accuracy for Underwater Crack Dataset	Validation Accuracy	Training Time	Epoch	Maximum Iterations	Iterations per Epoch	Frequency	Learning Rate
				SqueezeNet					
1.	Training—0.1, Testing—0.1, Validation—0.1	98.25%	99.12%	74 min 54 s	6	186	31	30 iterations	0.001
2.	Training—0.15, Testing—0.15, Validation—0.1	99.1%	99.20%	124 min 27 s	6	276	46	30 iterations	0.001
3.	Training—0.3, Testing—0.3, Validation—0.3	99.6%	99.45%	282 min 49 s	6	558	93	30 iterations	0.001
				AlexNet					
1.	Training—0.1, Testing—0.1, Validation—0.1	99.6%	99.62%	460 min 20 s	6	186	31	30 iterations	0.001
2.	Training—0.15, Testing—0.15, Validation—0.1	99.5%	99.47%	450 min 51 s	6	276	46	30 iterations	0.001
3.	Training—0.3, Testing—0.3, Validation—0.3	99.7%	99.67%	355 min 27 s	6	558	93	30 iterations	0.001

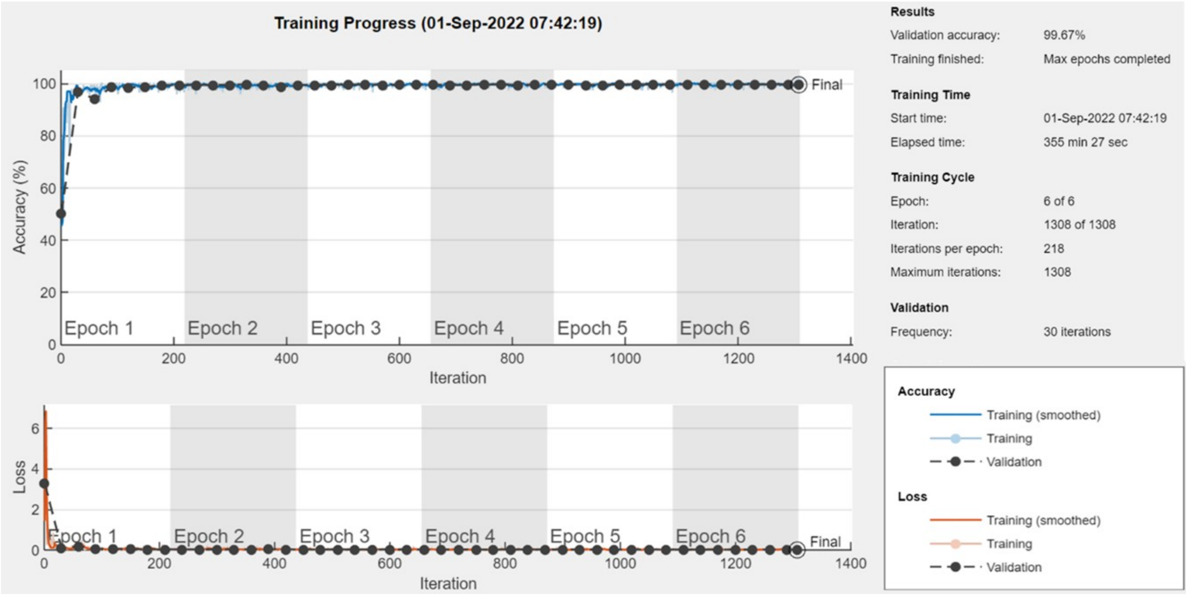


Figure 9. Training progress plots and training parameters for Case 3 using AlexNet, with training, testing, and validation data = 30% of the total dataset.

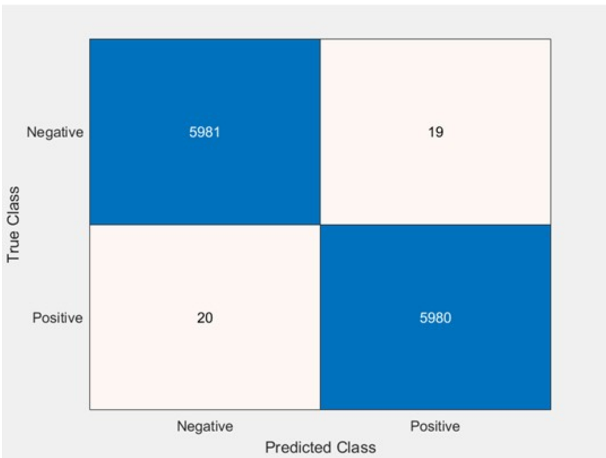


Figure 10. Confusion matrix with underwater crack images dataset (overall accuracy = 99.7%).

6. Conclusions

This paper focused on the development of an underwater crack detection system for structural integrity assessment of submerged structures, emphasizing the use of machine learning approaches. This highlights the significance of advanced technology in addressing the challenges associated with underwater crack detection.

The literature review conducted in the paper provides insights into the current methods for underwater surface crack detection, highlighting the existing challenges and potential opportunities for improvement. This suggests that the proposed system takes into account the limitations of current approaches and aims to overcome them.

The paper introduces an image augmentation approach for creating underwater optical effects. By utilizing augmented images, the proposed system enhances the performance of existing network-based machine learning approaches in detecting cracks in underwater conditions. This showcases the innovative use of data augmentation techniques to improve detection accuracy. The main innovations in this study are an augmented database and an improved underwater concrete crack detection technique.

The experimental results presented in the paper demonstrate the effectiveness and accuracy of the developed system in detecting cracks in underwater structures. This indicates that the proposed system has the potential to significantly contribute to the safety and reliability of submerged structures, such as offshore oil and gas installations, underwater pipelines, and underwater foundations for bridges and dams.

The implementation of the proposed system has the potential to prevent catastrophic failures by detecting cracks in underwater structures at an early stage. This emphasizes the importance of proactive maintenance and inspection strategies, which can ultimately save costs and ensure the long-term integrity of underwater infrastructure.

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