Computer Vision and Deep Learning for Fish Classification in Underwater Habitats: A Survey

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Funding information
This research is supported by an Australian Research Training Program (RTP) Scholarship.

Marine scientists use remote underwater video recording to survey fish species in their natural habitats. This helps them understand and predict how fish respond to climate change, habitat degradation, and fishing pressure. This information is essential for developing sustainable fisheries for human consumption, and for preserving the environment. However, the enormous volume of collected videos makes extracting useful information a daunting and time-consuming task for a human. A promising method to address this problem is the cutting-edge Deep Learning (DL) technology. DL can help marine scientists parse large volumes of video promptly and efficiently, unlocking niche information that cannot be obtained using conventional manual monitoring methods. In this paper, we provide an overview of the key concepts of DL, while presenting a survey of literature on fish habitat monitoring with a focus on underwater fish classification. We also discuss the main challenges faced when developing DL for underwater image processing and propose approaches to address them. Finally, we provide insights into the marine habitat monitoring research domain and shed light on what the future of DL for underwater image processing may hold. This paper aims to inform a wide range of readers from marine scientists who would like to apply DL in their research to computer scientists who would like to survey state-of-the-art DL-based underwater fish habitat monitoring literature.

KEYWORDS
Fish Habitat, Monitoring, Computer Vision, Deep Learning.
1 | INTRODUCTION

Understanding and modelling how fish respond to climate change, habitat degradation, and fishing pressure are critical for environmental protection, and are crucial steps toward ensuring sustainable natural fisheries, to support ever-growing human consumption [1]. Effective monitoring is a vital first step underpinning decision support mechanisms for identifying problems and planning actions to preserve and restore the habitats.

Marine scientists use underwater cameras to record, model, and understand fish habitats and fish behaviour. Remote Underwater Video (RUV) recording in marine applications [1] has shown great potential for fisheries, ecosystem management, and conservation programs [2]. With the introduction of consumer-grade high-definition cameras, it is now feasible to deploy a large number of RUVs or Autonomous Underwater Vehicles (AUVs) to collect substantial volumes of data and to perform more effective monitoring [3–5]. However, underwater habitats introduce diverse video monitoring challenges such as adverse water conditions, high similarity between fish species, cluttered backgrounds, and occlusions among fish. In addition, the volume of data generated by deployed RUVs and AUVs rapidly surpasses the capacity of human video viewers, making video analysis prohibitively expensive [6]. Moreover, humans are more prone to error than a well-designed machine-centred monitoring algorithm. Therefore, an automated, comprehensive monitoring system could significantly reduce labour expenses while improving throughput and accuracy, increasing the precision in estimates of fish stocks, fish distribution and biodiversity in general [7, 8]. Implementing such systems necessitates effective Computer Vision (CV) processes. As a result, significant research has been conducted on implementing monitoring tools and techniques that build upon CV algorithms for determining how fish exploit various maritime environments and differentiating between fish species [9].

In image analysis and CV domains, Deep Learning (DL) approaches have consistently produced state-of-the-art results in a variety of applications from agriculture [10] to medicine [11, 12] using Deep Neural Networks (DNNs) [13–15]. Many of DNN-based approaches outperform conventional methods in marine applications, including ecological and habitat monitoring, using video trap data [16, 17]. DL is a technique that mimics how people acquire knowledge by continuous analysis of input data. The main drivers of DNN success over the past decade have been architectural progress by a large community of computer scientists, more powerful computers and processors, and access to massive amounts of data, which is critical for developing successful generalizable DL applications.

DNNs have been successfully employed in many CV applications such as object classification, identification, and segmentation as a result of the invention of Convolutional Neural Network (CNN). CNN is a class of DNN, most commonly applied to visual analyses. For instance, CNNs have been successfully used for analysis of fish habitats [3, 6, 18]. In comparison to other image recognition algorithms, CNNs have the significant benefit that they require limited pre-processing. CNNs are not hand-engineered but uncover and learn hidden features in the data on their own. They learn level-by-level with various levels of abstraction. For instance, they learn simple shapes (edges, lines, etc.) in the first few layers, understand more sophisticated patterns in their next layers, and learn classes of objects in their final layers.

A putative challenge with CNNs is that they require a large number of images to be fully trained and generalise their learning to unseen scenarios. On the other hand, CNNs have
an interesting and powerful feature that enables transfer of their learning and knowledge across different domains. This means that they can be fine-tuned to work on new datasets (e.g. fish datasets) other than the one that they have been trained on (e.g. general objects).

Equipping CV algorithms with the powerful learning and inference capabilities of CNNs can provide marine scientists and ecologists with powerful tools to help them better understand and manage marine environments. However, although DL, and its variants such as CNNs, have been applied to various applications across a multitude of domains [19–21], their use in conjunction with computer vision for marine science and fish habitat monitoring is not broadly appreciated, meaning they remain under utilised. To address this, in this paper, we introduce key concepts and typical architectures of DL, and provide a comprehensive survey of key CV techniques for underwater fish habitat monitoring. In addition, we provide insights into challenges and opportunities in the underwater fish habitat monitoring domain. Although a recent survey reviews deep learning techniques for marine ecology [22] and briefly discusses DL-based fish image analysis, to the best of our knowledge, no comprehensive survey and overview of deep learning with a specific focus on fish habitat monitoring currently exist. Our paper tries to address this gap and to facilitate the application of modern deep learning approaches into the challenging underwater fish images analysis and monitoring domains.

2 | BACKGROUND TO COMPUTER VISION AND MACHINE LEARNING

Humans, have a natural ability to comprehend the three-dimensional structure of the world around us. Vision scientists [23] have spent decades attempting to understand how the human visual system functions [24]. Inspired by their findings, CV researchers [25–27] have also been working on ways to recover the 3D shape and appearance of objects from photos. The automatic retrieval, interpretation, and comprehension of useful information from a single image or collection of images can be referred to as CV. In another definition, CV is a field of Artificial Intelligence (AI) that focuses on training computers to detect, recognise, and understand images similarly to processes used by humans. This necessitates the development of logical and algorithmic foundations for automated visual understanding [28]. This understanding can include image classification, object localisation, object recognition, semantic segmentation, and instance segmentation, as shown in Figure 1. Today, computers with CV powers can extract, analyse, and interpret significant information from a single image or a sequence of images.

Despite this progress, the goal of making a computer to understand a picture at the same level as a two-year-old child remains unattainable. This is due, in part, to the fact that CV is an inverse problem in which we attempt to recover specific unknowns despite having inadequate knowledge to completely describe the solution. In CV applications, the cause is usually an exploration process, while the effects are the observed data. The corresponding forward problems then consist of predicting empirical data given complete knowledge of the exploration process. In some sense, solving inverse problems means "computing backwards", which is usually more difficult than forward problem solving [29].

The problem of backward computation was eased by the introduction of ML techniques more than 6 decades ago. However, in conventional ML approaches, the majority of complex features of the learning subject must be identified by a domain expert in order to decrease the complexity of the data and make patterns more evident for successful learning.
Machine Learning

Deep Learning

FIGURE 2 Comparison between Machine Learning (ML) and DL. In ML techniques, the features need to be extracted by domain expert while DL relies on layers of artificial neural networks to extract these features.

(see Figure 2-top). However, DL offered a fundamentally new method to ML. Most DL algorithms possess the groundbreaking ability of automatically learning high-level features from data with minimal or no human intervention (see Figure 2-bottom).

DL is based on neural networks, which are general-purpose functions that can learn almost any data type that can be represented by many instances. When you feed a neural network a large number of labelled instances of a certain type of data, it will be able to uncover common patterns between those examples and turn them into a mathematical equation that will assist in categorising future data. Empowered by this fundamental feature, DL and DNN have progressed from theory to practice as a result of advancements in hardware and cloud computing resources [12]. In recent years, DL approaches have outperformed previous state-of-the-art ML techniques in a variety of areas, with CV being one of the most notable examples.

Before the introduction of DL, the capabilities of CV were severely limited, necessitating a great deal of manual coding and effort. However, owing to improved research in DL and neural networks, CV is now able to outperform humans in several tasks related to object recognition and classification [30–33]. CV equipped with DL, is being used today in a wide variety of real-world applications, that include, but are not limited to:

- **Optical character recognition (OCR)** [34]: automatic number plate recognition and reading handwritten postal codes on letters;
- **Machine inspection** [35]: fast quality assurance inspection of components using stereo vision with advanced lighting to assess tolerance levels on aircraft wings or car body parts, or to spot flaws in steel castings using X-ray technology;
- **Retail** [36]: object detection for automatic checkout lanes;
- **Medical imaging** [37]: registration of preoperative and intra-operative imaging or long-term analyses of human brain anatomy as they age;
- **Automotive safety** [38]: detection of unforeseen objects such as pedestrians on the street (e.g. fully autonomously driving vehicles);
- **Surveillance** [39]: Monitoring of trespassers, studies of highway traffic, and monitoring pools for drowning victims;
- **Fingerprint recognition and bio-metrics** [40]: For both automatic entry authentication and forensic software.

This demonstrates the significant impact of DL on CV and demonstrates its potential for marine visual analysis applications.

3 | BACKGROUND TO DEEP LEARNING

Deep Learning (DL) [42,43] is a subset of ML algorithms that employs a neural network with several layers to very loosely replicate the function of the human brain by enabling it to "learn" from huge quantities of data. The learning happens when the neural network extracts higher-level features from input training data. The term "deep" refers to the usage of several layers in the neural network. Lower layers, for example in image processing, could detect edges, whereas higher layers might identify parts of the object.

3.1 | How Deep Learning differs from Machine Learning

Machine Learning (ML) is usually referred to as a class of algorithms that can recognise patterns in data and create pre-
A popular CNN architecture, named UNET [41] is demonstrated. The first component of UNET is the encoder, which is used to extract features from the input image. The second component is the decoder that outputs per-pixel scores. The network is composed of five different layers including convolutional (Conv Layer), Rectified Linear Unit (ReLU), Pooling, Deconvolutional (DeConv), and Softmax. Here, the task of the DNN layers has been to give a high score to only the pixels in the input image that belong to the fish body, resulting in the demonstrated white blobs output, showing where the fish are.

Deep Learning (DL) is a subclass of standard ML because it uses the same type of data and learning methods that ML applies. However, when dealing with unstructured data, e.g. text and images, ML usually goes through some pre-processing to convert it to a structured format for learning. DL, on the other hand, does not usually require the data pre-processing needed by ML. It is capable of recognising and analysing unstructured data, as well as automating feature extraction, significantly reducing the need for human knowledge (see Figure 2-bottom).

For example, to recognise fish in an image, ML requires that specific fish features (such as shape, colour, size, and patterns) be explicitly defined in terms of pixel patterns. This may be a challenge for non-ML specialists because it typically requires a deep grasp of the domain knowledge and good programming skills. DL techniques, on the other hand, skip this step entirely. Using general learning techniques, DL systems can automatically recognise and extract features from data. This means that we just need to tell a DL algorithm whether a fish is present in an image, and it will be able to figure out what a fish looks like given enough examples. Decomposing the data into layers with varying levels of abstraction enables the algorithm to learn complex traits defining the data, allowing for an automatic learning approach. DL algorithms may be able to determine which features (such as fishtail) are most important in differentiating one animal from another. Prior to DL, this feature hierarchy needed to be determined and created by hand by an ML expert.

### 3.2 How Deep Learning works

Deep Neural Network (DNN), also known as artificial neural network, is the basis of deep learning. DNNs use a mix of data inputs, weights, and biases to learn the data, by properly detecting, categorising, and characterising objects in a given dataset of interest. DNNs are made up of several layers of linked nodes, each of which improves and refines the network prediction or categorisation capabilities. For instance, Fig. 3 shows a popular DNN architecture for image processing, called UNET [41]. UNET, which is a fairly complex deep learning architecture, is composed of a few different components and layers, to achieve a specific learning goal, i.e. to segment fish body in an input image.

Any DNN is composed of three types of layers, namely input, output, and hidden layers. The visible layers are the input and output layers (see Figure 4). The DL model gets the data for processing in the input layer, and the final prediction or classification is generated in the output layer. In a typi-
Supervised learning is a method used to enable finding and optimising a function that maps an input to its corresponding output in an input-output object pair, also known as training example [45]. Supervised learning uses a set of training examples based on manually-labelled training data prepared by human observers or ‘supervisors’, hence the name for the learning method.

The aim of supervised learning is to generate an inferred function, \( f \), that maps to the training examples, and can then be used to map to new examples outside of the training examples. In order to accomplish any general task, a computer can be programmed to find function \( f \) to map \( X \) to \( Y \), \( i.e. \ (f : X \mapsto Y) \), where \( X \) is an input domain and \( Y \) is an output domain. For example, in an image classification task, \( X \) is the dataset of images and \( Y \) is a set of corresponding classification labels, which determine whether an object is present in the respective image in the dataset or not.

To determine the function \( f \) that can recognise, for instance, a fish in an image using DL, one solution is to do feature engineering. However, it is usually very difficult to perform this, \( i.e. \) hand-pick features of the fish, based on the domain knowledge that comes from the training dataset. In addition, most of the time, the hand-picked features need to be pruned to reduce their pixel dimensionality. Comparatively, it is often more feasible to collect a large dataset of \( (x, y) \in X \times Y \) to find the mapping function \( f \), and this affords supervised learning advantage as an alternative mapping technique compared with direct feature engineering. Specifically, in the fish classification task, a large dataset of fish images is collected, where each image \( x \) is labelled with \( y \) that shows the presence or absence of a fish, without the need to hand-pick its features.

One of the main supervised learning approaches is training a neural network, which is the foundation of deep learning, especially for computer vision applications such as fish image processing. We, therefore, dedicate the next subsection to neural networks and their underlying working principles.
3.4 | Neural Networks

A 'neural network' [46] is a computer program originally conceived by mimicking actual cerebral neural networks that make up the brain's grey matter. A computer's neural network, a.k.a. an artificial neural network, "learns" to do a specific task by using a large amount of data, usually through supervised network training that does not involve any task-specific rules. As briefly mentioned, a neural network is constructed from three types of layers: an input layer, hidden or latent layers, and an output layer (see Figure 4). These layers include processing neurons within them (coloured circles in Figure 4), and connecting synapses (weights) between them (edges in the figure).

The input layer is the gate to the network. It provides information to the network from outside data, and no calculation is made in this layer. Instead, input nodes pass the information on to the hidden layer. This layer is not visible to the outside world and serves as an abstraction of the inputs, independent of the neural network structure. The hidden layer (layers) processes the data received from the input layer and transfers the results to the output layer. Finally, the output layer brings the information that the network has learned into the outside world.

Learning in a neural network happens through minimising a loss function. Generally, a loss function is a function that returns a scalar value to represent how well the network performs a specific task. For example, in image classification, the network is expected to correctly classify all the images containing a fish as fish, and all those not including a fish, as no fish, returning a loss value of zero. During learning, the network receives a large amount of input data, e.g. thousands of fish images, and eventually learns to minimise the loss between its predicted output and the true target value. In the case of supervised learning, these true target values are provided to the network, to find function $f$ described in the previous section, to minimise the loss function. This minimisation happens through optimising $f$ using an algorithm such as Stochastic Gradient Descent (SGD) [47] that helps find network weights/parameters that minimise the loss.

3.5 | Convolutional Neural Network

CNNs are probably the most commonly used artificial neural networks. They have been the dominant deep learning tool in computer vision and have been widely used in underwater marine habitat monitoring [48]. CNNs are broadly designed after the neuronal architecture of the human cortex but on much smaller scales [49]. A CNN [50] is specifically designed for dealing with datasets that have some spatial or topological features (e.g. images, videos), where each of the neurons are placed in such a manner that they overlap and thus react to multiple spots in the visual field. A CNN neuron is a simple mathematical design of the human brain's neuron that is utilised to transform nonlinear relationships between inputs and outputs in parallel. There are two primary layer types in a CNN, i.e. convolutional layers and pooling layers, which generate feature maps, as explained in the following subsections.

3.5.1 | Convolutional Layer

In this layer, the convolutional processes (i.e., overlap among neuron inputs) are used on limited fields to avoid the need to learn billions of weights (parameters), which would be required if all the neurons in one layer are connected to all the neurons in the next layer. This excessive computation is avoided through the weight-sharing of convolutional layers combined with filters for their corresponding feature maps. In addition, weight-sharing is useful in avoiding model over-fitting, i.e. memorising the training data, [51], while also reducing computing memory requirements and enhancing learning performance [52].

3.5.2 | Pooling Layer

This layer is used to reduce the spatial dimension (not depth) of the input features and add control for avoiding overfitting by reducing the number of representations with a specified spatial size. Pooling operations can be done in two different ways, i.e. Max and Average pooling. In both methods (see Figure 5), an input image is down-scaled in size, by taking the maximum of 4 pixels and down-sampling them to one pixel. Pooling layers are systematically implemented
between convolutional layers in conventional CNN architectures. The pooling layers work on each channel (activation map) individually and downsample them spatially. By having fewer spatial information, pooling layers make a CNN more computationally efficient.

3.5.3 Feature Maps

Feature Maps, also called Activation Maps, are the result of applying convolutional filters or feature detectors to the preceding layer image. The filters are moved on the preceding layer by a specified number of pixels. For instance, in Figure 6, there are 37 filters of the size $3 \times 3$ that move across the input image with a stride of 1 and result in 37 feature maps.

The majority of CNN layers are convolutional layers. These layers are used to apply the same convolutional filtering operation to different parts of the image, creating “neurons” that can then be used to detect features, like the edges and corners. A collection of weights connects each neuron in a convolutional layer to the preceding layer’s feature maps, or to the input layer image. The feature maps help visualise the features that the CNN is learning to give an understanding of the network learning process, as shown in Figure 6.

4 | APPLICATIONS OF DEEP LEARNING IN FISH-HABITAT MONITORING

Although deep learning and CNNs can be used in a variety of marine applications such as automatic vessel detection [53] or for analysis of deep-sea mineral exploration [54], in this paper, we focus on using CNNs for CV tasks. These tasks are mainly designed to extract knowledge from underwater videos and images. Despite the recent use of CNNs for various visual analysis tasks such as segmentation [55–58], localisation [59–61], and counting [62–64], the most common and the widest studied CV task in underwater fish habitat monitoring has been classification. Therefore, in this paper, we focus mainly on classification of underwater fish images. We survey some of the latest works on fish classification and provide a high-level technical discussion of these works.

The task of classification is defined as classifying the input samples into different categories, usually based on the presence or absence of a certain object/class, in binary classification; or the presence of several different objects belonging to different classes, in multi-class classification [65]. Similarly, image classification is concerned with assigning a label to a whole image based on the objects in that image. Conceivably, an image can be labelled as fish, when there is a fish present in it, or negative when no fish is present. Similarly, images of different species should be automatically assigned...
to their respective classes or given a label representing their class.

Classification is a difficult process if done manually, because an image may need to be categorised into more than one class. In addition, there may be thousands of images to be classified, which makes the task very time-consuming and prone to human error. Consequently, automation can help perform classification quicker and more efficiently.

In the context of fish and marine habitat monitoring, CV offers a low-cost, long-term, and non-destructive observation opportunity. One of the initial tasks performed using deep learning on CV-collected marine habitat images is fish classification, which is a key component of any intelligent fish monitoring systems, because it may activate further processing on the fish image. However, underwater monitoring based on image and video processing pose numerous challenges related to the hostile condition under which the fish images are collected. These include poor underwater image quality due to low light and water turbidity, which result in low resolution and contrast. Additionally, fish movements in an uncontrolled environment can create distortion, deformations, occlusion, and overlapping. Many previous works [66–68] have tried to address these challenges. Some of these works focused on devising new methods to properly extract traditional low-level features such as colours and textures using mean shift algorithm [69], in the presence of the challenges. However, these works have not been very successful compared to DL approaches.

With the inception of CNNs, many researchers utilised them to extract both high-level and low-level features of input images. These features, which can be automatically detected by the CNN, carry extensive semantic information that can be applied to recognise objects in an image. In addition, CNNs have the ability to address the challenges outlined above. Therefore, they are currently the main underwater image processing tool in literature for fish classification, as shown in Tables 1 and 2. These tables list some of the latest classification works, while providing details about the DL models used and the framework within which the model was implemented. It also provides information about the data source, as well as the pre-processing of the data and its labels, while reporting the Classification Accuracy (CA) and a short comparison with other methods if the reviewed work has provided it. One of the main metrics when comparing different methods for classification is their CA, which is defined as the percentage of correct predictions by the network.

\[
CA = \frac{TP + TN}{TP + TN + FP + FN},
\]

where TP (True Positive) and TN (True Negative) represent the number of correctly classified instances, while FP (False Positive) and FN (False Negative) represent the number of incorrectly classified instances. For multi-class classification, CA is averaged among all the classes.
The works in Tables 1 and 2 can be divided into two general categories. The first category deals with designing effective CNNs that address the challenge of unconstrained, complex, and noisy underwater scenes, while the second category also tries to address the usual problem of limited fish training datasets.

As mentioned, when processing unconstrained underwater scenes specific attention should be paid to implementing a classification approach that is capable of handling variations in light intensity, fish orientation, and background environments, and similarity in shape and patterns among fish of various species.

In order to overcome these challenges and to improve classification accuracy, various works have devised different methodologies. In [70], the authors used different activation functions to examine the most suitable for fish classification, while in [30] different number of convolutional layers and different filter sizes were examined. In [31], the authors used a CNN model in a hierarchical feature combination setup to learn species-dependent visual features for better accuracy. In another work [32], principal-component analysis was used in two convolutional layers, followed by binary hashing in the non-linear layer and block-wise histograms in the feature pooling layer. Furthermore, a single-image super-resolution method was used in [33] to resolve the problem of limited discriminative information of low-resolution images. Moreover, [71] used two independent classification branches, with the first branch aiming to handle the variation of pose and scale of fish and extract discriminative features, and the second branch making use of context information to accurately infer the type of fish. The reviewed works show that depending on the type of environment and fish species similarities in the dataset under consideration, various techniques should be considered and investigated to find the best classification accuracy.

Dataset limitation, i.e. having limited number of fish images from different species, and/or having few numbers of different fish etc, is another challenge in underwater fish habitat monitoring in general and in fish classification, in specific. This challenge has been addressed in [48, 72–74] using transfer learning.

Transfer learning is a ML method that works by transferring information obtained while learning one problem or domain to a different but related problem or domain. Comparing a randomly initialised classifier with another one pre-trained on ImageNet [75], Saleh et al. [48] achieved a fish classification accuracy of 99%, outperforming the randomly-initialised classifier, significantly. This finding shows that transfer learning can bring learned information from the ImageNet learning domain to fish classification domain and can be a useful and crucial method for evaluating fish environments. Transfer learning was also used in [76] where general-domain above-water fish image learning was transferred and used for underwater fish classification. In the same way, to train large-scale models that are able to generate reasonable results, [77] collected 1000 fish categories with 54,459 unconstrained images from various professional fish websites and Google engine.

In addition to transfer learning, some works have developed specific machine learning techniques suited for their applications. For instance, in a previous study [78], a pre-trained CNN was used as a generalised feature extractor to avoid the need for a large amount of training data. The authors showed that by feeding the CNN-extracted features to a Support Vector Machine (SVM) classifier [79], a CA of 94.3% for fish species classification can be achieved, which significantly outperforms a stand-alone CNN achieving an accuracy of 53.5%. Also, [80] used the same techniques in [78] to achieve a CA of 98.79%. In addition, [81] developed a new technique for fish classification by modifying AlexNet [82] model with fewer number of layers. Moreover, [6] presented a labelling efficient method of training a CNN-based fish-detector on a small dataset by adding 27,000 above-water and underwater fish images.

CNNs are sometimes capable of surpassing human performance in identifying fish in underwater images. By training a CNN on 900,000 images, Villon et al. [83] could achieve a CA of 94.9% while human CA was only 89.3%. This result was achieved mainly because the CNN was able to successfully distinguish fish that were partially occluded by corals or other fish, while human could not. Furthermore, the best CNN model developed in [83] takes 0.06 seconds on average to identify each fish using typical hardware (Titan X GPU). This demonstrates that DL techniques can conduct accurate fish classification on underwater images cost-effectively and efficiently. This facilitates monitoring underwater fish and can advance marine studies concerned with fish ecology.
If DL methods are going to be deployed widely for different marine applications such as fish classification, there is a need to implement them efficiently, so that they can run on low-power embedded systems, which can run in real-time on mobile devices such as underwater drones. To that end, Meng et al. \cite{84} have developed an underwater drone with a panoramic camera for recognising fish species in a natural lake to help protect the environment. They have trained an efficient CNN for fish recognition and achieved 87% accuracy while requiring only 6 seconds to identify 115 images. This promising result shows that, DL can be used to classify underwater fish while also satisfying the real-time conditions of mobile monitoring devices. In addition, other efficient hardware design approaches that have proven useful in reducing power consumption and increasing speed in classification task in other domains such as agriculture \cite{85} can be adopted on edge underwater processors.

5 | CHALLENGES AND APPROACHES TO ADDRESS THEM

5.1 | Model Generalisation

One of the most difficult challenges in DL is to improve deep convolutional networks generalisation abilities. This refers to the gap between a model’s performance on previously observed data (i.e. training data) and data it has never seen before (i.e. testing data). A wide gap between the training and validation accuracy is usually a sign of overfitting. Overfitting occurs when the model accurately predicts the training data, mostly because it has memorised the training data instead of learning their features.

One way to monitor overfitting is by plotting the training and validation accuracy at each epoch during training. That way, we will see that if the gap between the validation and training accuracy/error is widening (over- or under-fitting) or narrowing (learning). A well-known and effective method for improving the generalisability of a DL model is to use regularisation \cite{87}. Some of the regularisation methods applied to fish and marine habitat monitoring domains include transfer learning \cite{88}, batch normalisation \cite{57}, dropout \cite{81}, and using a regularisation term \cite{62}.

5.2 | Dataset Limitation

Another challenge of training deep learning models is the limited dataset. Deep learning models require enormous datasets for training. Unfortunately, most datasets are large, expensive, and time-consuming to build. For this reason, model training is usually conducted by collecting samples from a small number of datasets, rather than from a large number of datasets.

A dataset can be categorised into two parts: labelled data and unlabeled data. The labelled data is the set of data that needs the labelling of classes, e.g. fish species in an image, or absence or presence of fish in an image. The unlabeled data is the set of data that has not been processed. The labelled data forms the training set whose size is closely related to the accuracy of the trained model. The larger the training set, the more accurate the trained model. Large training set, however, are expensive to build. They require a large number of resources, such as people-hours, space, and money, making it very difficult for many researchers to achieve them, and in turn hinders their research.

Since it is difficult to obtain a large labelled dataset, various techniques have been proposed to address this challenge. Some of the techniques applied to the fish and marine habitat monitoring domains include transfer learning \cite{89}, data augmentation \cite{30, 48}, using hybrid features \cite{90–92}, weakly supervised learning \cite{93}, and active learning \cite{94}.

5.3 | Image Quality

Underwater image recognition’s average accuracy lags significantly behind that of terrestrial image recognition. This is mostly owing to the low quality of underwater photos, which
| Article | DL Model | Framework | Data | Annotation/Pre-processing/Augmentation | Classes and Labels | Perf. Metric | Metric Value | Comparisons with other methods |
|---------|----------|-----------|------|----------------------------------------|--------------------|--------------|--------------|---------------------------------|
| Recognition of Fish Categories Using Deep Learning Technique [70] | CNN | Keras, Tensorflow | Authors-created dataset containing 560 fish images, 400 training and 160 test images. | Each image is assigned the fish species name as a label | 10 classes of 10 different fish species | CA | 95% | NA |
| Comparison of Different DL Structures for Fish Classification [30] | CNN | Torch | The public QUT fish dataset contains 3960 images of 468 fish species in different environments. | Each image is assigned the fish species name as a label | 468 classes of 468 different fish species | CA | 46.02% | NA |
| Fish Species Classification in Unconstrained Underwater Environments Based on DL [31] | CNN | NA | The images are from the public Fish4Knowledge dataset (LifeCLEF 2014, LifeCLEF 2015) | Each image is assigned the fish species name as a label | 25 classes of 25 different fish species | CA | 96.75% | Comparison with the conventional SVM machine learning tool that achieved 83.94% |
| Deep-Fish: Accurate Underwater Live Fish Recognition with a DL Architecture [32] | CNN | Matlab | The images are from the public Fish4Knowledge dataset | Each image is assigned the fish species name as a label | 23 classes of 23 Different fish species | CA | 98.64% | Comparison with conventional machine learning tools as baseline methods achieving 93.58% |
| Fish Recognition from Low-resolution Underwater Images [33] | CNN | NA | 93 videos from LifeCLEF 2015 fish dataset | Each image was annotated by drawing a bounding box and labelling by species name | 15 classes of 15 different fish species | CA | 76.57% | Authors used the traditional gabor features and dense sift features that generated CA of 38.28% and 28.63%, respectively. |
| Automatic Fish Classification System Using DL [71] | CNN | NA | Eight target categories: Albacore tuna, Bigeye tuna, Yellowfin tuna, Mahi Mahi, Opah, Sharks, Other. | Each image is assigned the fish species name as a label | 8 classes of 8 different fish species | CE | 0.578, 1.387 | Ranked 17th on Kaggle leaderboard on test set at stage 1 and 16th at stage 2. |
| A Realistic Fish-habitat Dataset to Evaluate DL Algorithms For Underwater Visual Analysis [48] | ResNet-50 | Pytorch | Authors-created database containing 39,766 images from 20 habitats in remote coastal marine environments of tropical Australia | point-level and semantic segmentation labels | 20 classes of 20 different fish species | CA | 0.99 | NA |
| Deep Learning for Underwater Image Recognition in Small Sample Size Situations [72] | CNN | Caffe | The images are from the public Fish4Knowledge dataset | Each image is assigned the fish species name as a label | 10 classes of 10 different fish species | CA | 85.08% | NA |
| Underwater Fish Species Classification using CNN and DL [73] | CNN | NA | 27000 images from the public Fish4Knowledge dataset | Each image is assigned the fish species name as a label | 23 fish classes | CA | 96.29% | NA |
| Article                                                                 | DL Model          | Framework        | Data                                           | Classes and Labels | Perf. Metric | Comparisons with other methods |
|------------------------------------------------------------------------|-------------------|------------------|-----------------------------------------------|--------------------|--------------|---------------------------------|
| Underwater Live Fish Recognition by Deep Learning [74]                | CNN               | Keras, Tensorflow| Author's created dataset containing 50,000 images from various professional websites and Google search engine | 50 classes of fish species name as a label | CA 91.5%     | NA                              |
| Underwater Fish Detection with Weak Multi-Domain Supervision [86]     | CNN               | Caffe            | Author's created dataset containing over 50,000 images from over 50 reef sites around the Mayotte island | 2 classes          | CA 99.15%    | NA                              |
| A Deep Learning Method for Accurate and Fast Identification of Coral Reef Fishes in Underwater Images [83] | CNN               | NA               | Authors-created dataset of 450,000 images from over 50 reef sites around the Mayotte island | 20 classes of different fish species | CA 94.9%     | Comparing accuracy to human experts. The rate of correct identification was 94.9%, greater than the rate of correct identification by humans (89.3%). |
| Underwater Drone With Panoramic Camera for Automatic Fish Recognition Based on Deep Learning [84] | CNN               | NA               | Authors-created dataset containing 50,000 images from various professional websites and Google search engine | 50 classes of fish species name as a label | CA 87%       | NA                              |
| Underwater Fish Recognition by Deep Learning [77]                     | CNN               | Keras, Tensorflow| 35000 images from the public Fish4Knowledge dataset | 23 classes of fish species name as a label | CA 98.79%    | NA                              |
| WildFish++: A Comprehensive Fish Benchmark for Multimedia Research [77] | CNN               | Keras, Tensorflow| 120 10-second video clips of 16 species from Western Australia during 2011 to 2013 | 16 classes of 16 different fish species | CA 90.48%    | Comparing their proposed modified AlexNet achieving a CA of 90.48% with original AlexNet CA of 86.65% |
| Automatic Fish Species Classification in Underwater Videos: Exploring Pre-trained DNN Models to Compensate for Limited Labeled Data [78] | CNN               | Tensorflow       | The dataset contains 50 to 100 10-second video clips of 16 species from Western Australia during 2011 to 2013 | 23 classes of fish species name as a label | CA 89.0%     | Comparison of their proposed method of CNN+SV classifier achieving a CA of 89.0% with two previous works; SRC (Hsiao et al. [86]), 49.1% and CNN (Salman et al. [31]), 53.5% |
| Underwater Fish Species Recognition Using Deep Convolutional Neural Networks [81] | CNN               | Tensorflow       | The images are from two public datasets: QUT Fish4Knowledge dataset and LifeClef-15 | 6 classes of 6 different fish species | CA 90.48%    | Comparing their proposed modified AlexNet achieving a CA of 90.48% with original AlexNet CA of 86.65% |
| Automatic Fish Species Classification Using Deep Learning Techniques [80] | CNN               | Tensorflow       | The images are from two public datasets: QUT Fish4Knowledge dataset and LifeClef-15 | 6 classes of 6 different fish species | CA 89.0%     | Comparing accuracy to human experts. The rate of correct identification was 89.0%, greater than the rate of correct identification by humans (83.9%). |
| Underwater Fish Species Recognition Using Deep Learning Techniques [80] | CNN               | Tensorflow       | The images are from two public datasets: QUT Fish4Knowledge dataset and LifeClef-15 | 6 classes of 6 different fish species | CA 89.0%     | Comparing accuracy to human experts. The rate of correct identification was 89.0%, greater than the rate of correct identification by humans (83.9%). |
| WildFish++: A Comprehensive Fish Benchmark for Multimedia Research [77] | CNN               | Keras, Tensorflow| 54,650 labelled images from various professional websites and Google search engine | 23 classes of fish species name as a label | CA 99.15%    | NA                              |
| Automatic Fish Species Classification in Underwater Videos: Exploring Pre-trained DNN Models to Compensate for Limited Labeled Data [78] | CNN               | Tensorflow       | The dataset contains 50 to 100 10-second video clips of 16 species from Western Australia during 2011 to 2013 | 23 classes of fish species name as a label | CA 89.0%     | Comparison of their proposed method of CNN+SV classifier achieving a CA of 89.0% with two previous works; SRC (Hsiao et al. [86]), 49.1% and CNN (Salman et al. [31]), 53.5% |
| Underwater Fish Recognition by Deep Learning [74]                     | CNN               | Keras, Tensorflow| 27,000 images from the public Fish4Knowledge dataset | 23 classes of fish species name as a label | CA 99.45%    | NA                              |
| WildFish++: A Comprehensive Fish Benchmark for Multimedia Research [77] | CNN               | Keras, Tensorflow| 54,650 labelled images from various professional websites and Google search engine | 23 classes of fish species name as a label | CA 99.15%    | NA                              |
| Automatic Fish Species Classification in Underwater Videos: Exploring Pre-trained DNN Models to Compensate for Limited Labeled Data [78] | CNN               | Tensorflow       | The dataset contains 50 to 100 10-second video clips of 16 species from Western Australia during 2011 to 2013 | 23 classes of fish species name as a label | CA 89.0%     | Comparison of their proposed method of CNN+SV classifier achieving a CA of 89.0% with two previous works; SRC (Hsiao et al. [86]), 49.1% and CNN (Salman et al. [31]), 53.5% |
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| Automatic Fish Species Classification in Underwater Videos: Exploring Pre-trained DNN Models to Compensate for Limited Labeled Data [78] | CNN               | Tensorflow       | The dataset contains 50 to 100 10-second video clips of 16 species from Western Australia during 2011 to 2013 | 23 classes of fish species name as a label | CA 89.0%     | Comparison of their proposed method of CNN+SV classifier achieving a CA of 89.0% with two previous works; SRC (Hsiao et al. [86]), 49.1% and CNN (Salman et al. [31]), 53.5% |
frequently exhibit blurring, and colour deterioration, caused by the physical characteristics of the water and the hostile underwater environment.

Most CV applications perform some initial preprocessing of images before feeding them to their image processor. In underwater scenarios, these preprocessing techniques are typically used to enhance the image quality. Preprocessing can also help with the red channel information loss problem, which is required for obtaining relevant colour data. Another issue that arises in the remote underwater detection of a specific target in an image is the fact that multiple pixels can potentially be activated in the image. Multiple detection’s of the same target within the image is possible due to, for example, a moving target, changes in the underwater environment or a combination of both.

Preprocessing of underwater photos has been extensively researched, and several solutions have been devised for correcting typical underwater image artefacts [95, 96]. However, the image quality produced by these approaches is subjective to the observer, and because acquisition settings vary so widely, these methods may not be applicable to all datasets. According to empirical results [97, 98], the current tendency appears to be to perform picture repair and enhancement processes based on the dataset, i.e. determining the most appropriate preprocessing strategy for a specific dataset.

In addition, basic image enhancement techniques have been shown to be effective in improving image quality. For instance, in [91] increasing the uniformity of the background was used to boost picture contrast in underwater images for marine animal classification. This is a strong indicator that simple enhancing approaches might result in increased performance. Furthermore, some recent studies have employed DL algorithms to enhance image quality using low-quality images. In [99], for example, end-to-end mapping is performed between low-resolution and high-resolution images.

When compared to state-of-the-art handcrafted and traditional image enhancement methods, DL-based algorithms typically perform better in addressing picture quality in terrestrial photos. However, significant new research is required to customise these DL-based techniques for underwater images and maritime datasets. This poses as a future research opportunity for image quality enhancement in fish monitoring applications. Below, we discuss some more opportunities.

6 OPPORTUNITIES IN APPLICATION OF DL TO FISH HABITAT MONITORING

New methods and techniques will need to be devised to improve the accuracy of deep learning models for various marine habitat monitoring applications and to bring them closer to their terrestrial counterparts.

6.1 Spatiotemporal and Image Data Fusion

Most of the current marine habitat monitoring and visual processing tools only use image-based data to train their model to understand the habitats and monitor the environment. In such tools, each frame or image is separately processed and spatiotemporal correlations across neighbouring frames are simply overlooked. Exploiting this extra information and fusing it with the image-processing model can be beneficial.

Future works should consider including spatiotemporal information in training their model and understanding the scene. In particular, approaches similar to Long short-term memory (LSTM) networks or other RNN models can be used in conjunction with CNNs, to obtain improved classification or prediction outcomes by taking advantage of the time-domain information.

For instance, estimating and monitoring fish development based on previous continuous observations, and analysing fish behaviour are some of the applications where time domain information will be not only useful but also critical. Such models can also be used to build novel video-based protocols for the surveillance of critically endangered reef fish biodiversity.

6.2 Underwater Embedded and Edge Processing

DNNs have proven to be successful in both industry and research in recent years, particularly for CV tasks. Specifically, large-scale DL models have had a lot of success in real-world scenarios with large-scale data. This is mainly due to their capacity to encode vast amounts of data and handle millions of model parameters that enhance generalisation performance.
when new data is evaluated. However, this high computational complexity and substantial storage requirement makes them difficult to use in real-time applications, especially on devices with restricted resources (e.g. embedded devices and underwater edge processors for online monitoring). One approach to address this is to use compressed networks such as binarised neural networks, which have shown promise toward reaching low-power and high-speed edge inference engines [85], for near-underwater-sensor processing. This can significantly improve underwater image analysis capabilities, because the collected large-volume images do not need to be transferred to surface for processing, and only the low-volume results can be communicated to shore. This also solves another problem, which is the challenging underwater communication [100].

6.3 | Combining Data from Multiple Platforms

The use of different data collection platforms such as autonomous underwater vehicles (AUVs) or occupied submarines, can provide different image data from different perspectives of the same or different underwater habitats, to train more effective DNNs. In addition, using simultaneous data from multiple platforms can give more monitoring information, for instance, of fish distribution patterns, especially in situations where the number of platforms is limited. However, combining data from multiple platforms introduces some challenges such as the lack of ground truth (e.g., the number of fish in the sampled area for all the platforms), and the need to develop techniques that can integrate these data in a robust manner. Future research can work toward addressing these challenges to exploit the significant benefits of multiple platform data combination.

6.4 | Automated Fish Measurement and Monitoring

DL can be used to achieve automated fish measurements, which may be useful in underwater fish monitoring, for instance to survey fish growth and abundance. In addition, automated measurements can realise remote fish assessments, for example when the monitoring locations are remote, or the environmental conditions and or potential hazards do not allow frequent underwater scouting by human.

DL can also be used for automation of monitoring of other fish biological variables such as their dynamics, present species, and their abundance and biomass. On top of these, DL can be used to automate understanding of environmental and habitat features. To achieve these, new datasets should be collected, and new or existing DL techniques should be devised or customised in future research.

7 | CONCLUSION

Deep Learning (DL) sits at the forefront of the machine learning technologies providing the processing power needed to enable underwater video to fulfill its promise as a critical tool for visual sampling of fish. It offers efficient and accurate solutions to the challenges of adverse water conditions, high similarity between fish species, cluttered backgrounds, occlusions among fish, that have limited the spatio-temporal consistency of underwater video quality. As a result, DL, complemented by many other advances in monitoring hardware and underwater communication technologies, opens the way for underwater video to provide comprehensive fish sampling. This can span from shallow fresh and marine waters to the deep ocean, opening the way for the development of the truly comparative understanding of marine and aquatic fish fauna and ecosystems that has hitherto been impossible. At least as importantly, DL solves the problem of handling the vast quantities of data produced by underwater video in a consistent and cost-effective way, converting a prohibitively expensive activity into a simple issue of computer processing. By enabling the processing of vast quantities of data, DL allows underwater fish video surveys to be conducted with unprecedented levels of spatial and temporal replication enabling the massive knowledge advances that flow from the ability of underwater videos to be deployed contemporaneously across many habitats, and at many spatial scales, or to provide continuous data over time.

DL, and associated techniques, have the potential for widespread use in marine habitat monitoring for (1) data classification and feature extraction to improve the quality of automatic monitoring tools; or (2) to provide a reliable means
of surveying fish habitats and understanding their dynamics. While this will allow marine ecosystem researchers and practitioners to increase the efficiency of their monitoring efforts, effective development of DL will require concentrated and coordinated data collection, model development, and model deployment efforts, as well as transparent and reproducible research data and tools, which help us reach our target sooner.

ACKNOWLEDGEMENT

This research is supported by an Australian Research Training Program (RTP) Scholarship.

CONFLICT OF INTEREST

You may be asked to provide a conflict of interest statement during the submission process. Please check the journal’s author guidelines for details on what to include in this section. Please ensure you liaise with all co-authors to confirm agreement with the final statement.

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