Aquaculture, Fish and Fisheries

WILEY

AQUACULTURE, FISH and FISHERIES Open Access

REVIEW ARTICLE OPEN ACCESS

Machine Vision Applications for Welfare Monitoring in Aquaculture: Challenges and Opportunities

Amy Fitzgerald[1] | Christos C. Ioannou[2] | Sofia Consuegra[1,3] | Andrew Dowsey[4] | Carlos Garcia de Leaniz[1,5]

[1]Department of BioSciences, Swansea University, CSAR, Swansea, UK | [2]School of Biological Sciences, University of Bristol, Bristol, UK | [3]Instituto de Investigacións Mariñas (IIM-CSIC), Vigo, Spain | [4]Bristol Veterinary School, University of Bristol, Bristol, UK | [5]CIM, Universidade de Vigo, Vigo, Spain

Correspondence: Carlos Garcia de Leaniz (c.garciadeleaniz@swansea.ac.uk)

Received: 22 October 2024 | **Revised:** 5 January 2025 | **Accepted:** 7 January 2025

Funding: This study was funded by Swansea University; HORIZON EUROPE Framework Programme 101084651; Royal Society Industry Fellowship IF\R1\231030 (to SC).

Keywords: algorithm | artificial intelligence | computer vision | fish farm | non-invasive

ABSTRACT

Increasing consideration of welfare in aquaculture has prompted interest in non-invasive methods of monitoring that avoid unnecessary stress and handling. Machine vision (MV) provides a potential solution to these needs, as it can be used for non-invasive monitoring of animal health and welfare in real-time. We examined the practical applications of MV for welfare monitoring in aquaculture, the hardware and algorithms used for automated data collection, and the main challenges and solutions for data processing and analysis. The most common application of MV has been the estimation of size-related metrics (growth, biomass) in fish, but key aspects of welfare, such as monitoring of parasites and disease or detection of stress-related behaviours, are lagging behind. Numerous camera setups have been used, ranging from single to stereoscopic cameras and from emersed to submerged cameras, but these have often been used under optimal conditions that may not always reflect those prevalent in industry (high densities, low visibility), likely overestimating performance. Object detection algorithms, such as YOLO, have been the approach of choice for most MV applications in aquaculture, but our review has identified an increasing number of alternatives that can help circumvent some of the challenges posed by high densities and poor lighting typical of commercial farms. MV has the potential to transform welfare monitoring in aquaculture, but there are still important challenges that need to be overcome before it can become mainstream, namely the ability to detect ectoparasites and diseases, identify abnormal behaviours, and work across taxa, particularly in crustaceans.

1 | Introduction

Animal welfare refers to ‘the physical and mental state of an animal in relation to the conditions in which it lives and dies’, a definition that typically considers five domains: nutrition, physical environment, health, behavioural interactions and mental state (Barreto et al. 2022). One of the difficulties in measuring the welfare of aquatic organisms is that many current methods, especially those that involve monitoring individuals, are time consuming, invasive and stressful for the organisms (López-Patiño et al. 2014). The aquaculture sector has seen exponential growth in recent years, which has resulted in increased demands by legislators and the public for better welfare standards (Council of Europe 2006; Browman et al. 2019) and ethically produced food (Sebastiani, Montagnini, and Dalli 2013), especially in northern Europe (Bacher 2015). This increased pressure and the official acknowledgement of the sentience of both fish and decapod crustaceans (UK Public General Acts 2022) has created a need for novel methods of monitoring all five welfare domains.

BOX 1 | Key concepts in machine vision

An artificial neural network (ANN) is a non-linear mathematical function that takes a set of inputs and transforms them into an output depending on a set of parameters called weights, which are determined by training the network (Bishop 1994). Neural networks are made up of many artificial neurons, each processing multiple inputs and generating outputs. The simplest neural network is known as a single-layer perceptron (SLP) or a neuron, which takes multiple inputs, produces input weights, sums them and then passes the sum through a non-linear activation function to produce one or more outputs. However, the use of SLPs is limited as they can only produce binary outputs. To overcome this shortcoming, multi-layer perceptrons (MLPs) were developed, consisting of an input layer, an output layer and one or more hidden layers made of multiple neurons, with each layer being fully connected to the next one. MLPs can handle non-linear relationships. Both SLPs and MLPs are feed-forward networks; that is, data goes in only one direction, from the input nodes to the output nodes. Machine learning uses backpropagation (Rumelhart, Hinton, and Williams 1986), so that data is fed back into the network and the weights are updated each time the data passes through the network, until the error between the predicted and actual value cannot be further minimised. This is how neural networks are trained. Convolutional neural networks (CNNs) are a form of ANNs specifically used for machine vision due to their ability to recognise patterns in video and images (Patel and Patel 2020). More specifically, a CNN has one or more convolutional layers which act as feature extractors (Z. Li, Liu, et al. 2022). A convolutional layer breaks an image into overlapping tiles by passing a window (of a chosen size) over the image. This creates feature maps—the output of a CNN. After this, the feature maps go through pooling (usually either maxi pooling or average pooling), which allows the network to reduce the dimensions of the data while still allowing the network to extract important features. Not all neurons in the convolutional layers are fully connected, and this helps speed up convergence (Z. Li, Liu, et al. 2022). Different forms of CNN are used for machine vision tasks, many of which are publicly available—such as YOLO (Jiang et al. 2021), which should help increase uptake of machine vision by the aquaculture industry.

A common way to monitor welfare is through the use of operational welfare indicators (OWIs), that is, practical and easy-to-use metrics of welfare that can be used in a farm setting (Gutierrez Rabadan et al. 2021). However, monitoring of many OWIs (such as measuring growth or physical condition) often requires the removal of individuals from the water. Aquaculture species differ in their ability to withstand capture and handling, but air exposure is stressful to most farmed fish (Arends et al. 1999; Cook et al. 2015) and crustaceans (Stoner 2012) and negatively impacts their welfare (Barreto et al. 2022; Rey Planellas and Garcia de Leaniz 2024). Given that most farmed aquatic species—including all fish, decapod crustaceans and cephalopod molluscs—are now considered sentient animals (Birch et al. 2021), the use of MV to reduce handling stress and monitor welfare has ethical implications for the development of more sustainable, profitable and efficient aquaculture (O'Donncha and Grant 2019; Ashraf Rather et al. 2024).

Artificial intelligence (AI), specifically machine vision (MV), provides a powerful tool for non-invasive, underwater monitoring of aquatic organisms at the farm that can eliminate air exposure and handling, reducing stress, improving growth and welfare (Martínez-Vázquez et al. 2019). The use of AI has increased in recent years in a wide range of industries, including manufacturing (L. Zhou, Zhang, and Konz 2023), the healthcare sector (D. Lee and Yoon 2021) and the aquaculture industry (C.-C. Chang, Wang, et al. 2021; P. Lee 2000), reflecting improvements in software and the hardware required to run increasingly demanding computational tasks (Abu Talib et al. 2021). Central to the development of automatic object recognition is the use of machine learning (ML), a common type of AI that can perform complex tasks without explicit programming and is capable of self-improvement through data analysis (Jordan and Mitchell 2015; Janiesch, Zschech, and Heinrich 2021).

It has been argued that the use of artificial neural networks, a type of ML inspired by the working and complexities of the human brain (Zou, Han, and So 2008) (Box 1), has paved the way for the fourth industrial revolution, where improvements in efficiency will be achieved through 'smart manufacturing' (Rai et al. 2021) and also through precision food production (Antonucci and Costa 2020; Føre et al. 2018). MV (the successor of computer vision) uses ML to identify features such as textures, shapes and distances from images or videos (Fernandes et al. 2020) and was first explored in the early 1960s (Shapiro 2020), although classical computer vision did not originally use ML. MV has exploded in functionality through the use of ML and, more recently, deep learning using layered artificial neural networks and is already used in many disparate, real-world applications, ranging from the detection of cancer cells (W. He et al. 2022; Pacal et al. 2020) to the operation of self-driving cars (Badue et al. 2021). However, applications in aquaculture are relatively recent and have largely been restricted to the estimation of body size and biomass (Figure 1), generally under laboratory or optimal conditions, which can vary greatly from industry settings, where visibility can be poor and densities high.

MV can reduce manual labour and processing time (Wu et al. 2022; P. Lee 2000) and allows for real-time monitoring (Mandal and Ghosh 2024), which is essential for the assessment of animal health (Vo et al. 2021; D. Li, Wang, et al. 2022) and the detection of changes in behaviour (Barbedo 2022). Recent improvements in hardware for computer vision (Pang 2022) have made it more accessible to industry, and aquaculture is predicted to become one of the most important beneficiaries of such technological improvements. The use of MV in the aquaculture sector can increase efficiency and sustainability through the automation of tasks such as food delivery, water quality monitoring and welfare assessment in a move towards 'smart aquaculture'—the integration of smart devices and AI for monitoring and automatic decision making (Vo et al. 2021). This will aid the industry in meeting increasing global demands for fish, a sector which is projected to account for 55% of all fish production worldwide by 2032 (OECD 2023). As there are now commercially available MV systems for aquaculture (Korus et al. 2024), the potential

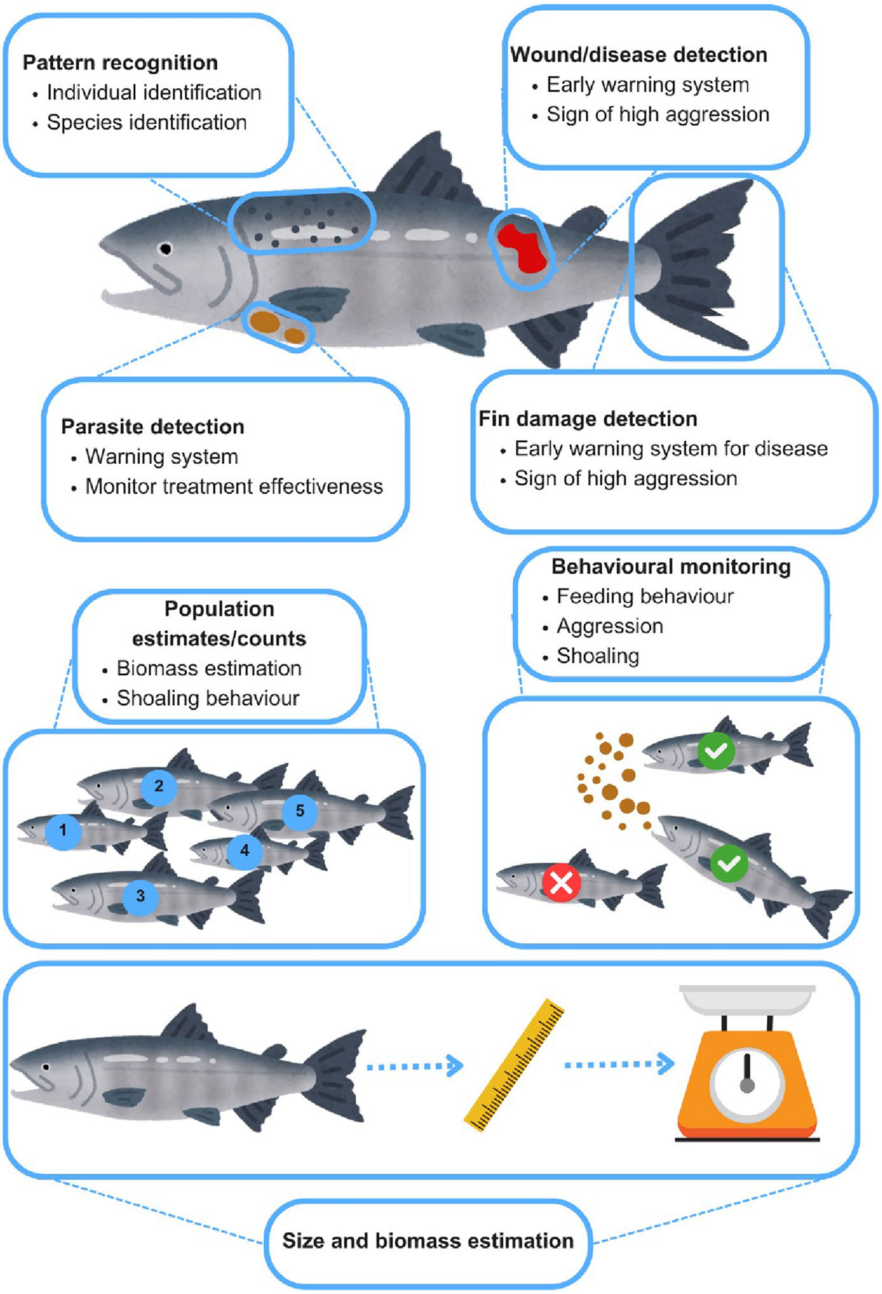

FIGURE 1 | Applications of machine vision for welfare monitoring in aquaculture include pattern recognition(Cisar et al. 2021), detection of wounds, disease and fin damage (Gupta et al. 2022), detection of ectoparasites (Kim, Choe, and Zhang 2023), count and population estimates (S. Zhang, Yang, et al. 2020), behavioural monitoring (J. Huang et al. 2022) and size and biomass estimation (Bravata et al. 2020).

economic benefits will be seen in the near future. It is also possible for MV to be integrated with other non-invasive monitoring techniques, including acoustic telemetry (Puig-Pons et al. 2019). Yet, despite its many potential benefits, there are no MV standards for data collection or algorithm design, which may be hampering progress. For example, although there are numerous protocols for data collection and camera setups, some of which require specialist knowledge (Saberioon et al. 2017), there is little practical guidance on which MV setups work best under commercial conditions, how to increase their accuracy or how they can be used for welfare monitoring. Here, we review the practical applications of MV for welfare monitoring in aquaculture, introduce the techniques, algorithms, and equipment used, and discuss the main challenges and limitations.

2 | Methods

To build the study corpus on the use of MV in aquaculture, we used the PRISMA protocol (Page et al. 2021) to search the Web of Science (all databases) and Google Scholar. For Google Scholar, the first 200 papers were considered, and all searches were carried out in an incognito window to increase reproducibility and reduce biases from previous searches. The timeframe was 01 January

2000–31 December 2023. The search terms we used were: 'AI OR "Artificial Intelligence" OR "Machine Learning" OR "machine vision" OR "computer vision" OR contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI AND Aquaculture OR "fish farm*" AND Welfare OR "welfare monitoring" AND fish OR prawn* OR shrimp', 'Aquaculture OR "fish farm*" AND Welfare OR "Welfare monitoring" AND fish OR prawn* OR shrimp AND contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI", "Aquaculture OR "fish farm*" AND Welfare OR "Welfare monitoring" AND fish OR prawn* OR shrimp AND weigh* OR biomass OR mass OR BMI', 'Aquaculture OR "fish farm*" AND Welfare OR "Welfare monitoring" AND contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI', 'Aquaculture OR "fish farm*" AND Welfare OR "Welfare monitoring" AND weigh* OR biomass OR mass OR BMI', 'Aquaculture OR "fish farm*" AND fish OR prawn* OR shrimp AND contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI', 'Aquaculture OR "fish farm*" AND contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI', 'Aquaculture OR "fish farm*" AND weigh* OR biomass OR mass OR BMI', 'AI OR "Artificial Intelligence" OR "Machine Learning" OR "machine vision" OR "computer vision" OR contactless OR nonintrusive AND weigh* OR biomass OR mass OR BMI'. The inclusion criteria included publications that (1) were written in English; (2) used MV (from video or images from cameras) on animals, not on the environment; (3) that specified the trait(s) being tracked or measured; (4) that included details of the software used or listed the techniques used to create the AI/algorithm and the metrics used to assess performance; (5) that were applied or could potentially be applied to aquaculture; (6) that were available online and open access and (7) that were primary literature (i.e., we excluded reviews). Of over 1.2 million potential studies, +74,000 were screened through a keyword search using the refine search function in Web of Science on the studies saved from the initial searches, and 278 were deemed eligible (Figure 2).

3 | Results and Discussion

3.1 | Uses of MV in Aquaculture

Of 278 eligible studies, 79 publications (28%) were identified that met the PRISMA inclusion criteria, 78% of which were published over the period 2021–2023; Figure 3). The sharp increase in MV studies is likely caused by improvements in graphics processing units and AI chips over the last decade (Momose, Kaneko, and Asai 2020) and integrated circuits developed specifically by Nvidia, Google and Intel to run deep neural networks (Pang 2022).

Size estimation was the most common application of MV in aquaculture (44%; Table 1), likely due to the direct commercial importance of monitoring growth performance and the need to detect stunted individuals resulting from stress, malnutrition (Barton, Schreck, and Barton 1987) or loss of water quality (Abdel-Tawwab et al. 2019). Size estimation is paramount in fish farming, and this has prompted the development of cameras and software for biomass estimation, mainly in salmon farming. Some examples include ReelBiomass (https://www.reeldata.ai/reelbiomass) and BiomassPro (https://www.innovasea.com/aquaculture-intelligence/biomass-estimation/). In comparison, we only found one study that used MV to estimate body mass in shrimp (Setiawan, Hadiyanto, and Widodo 2022), despite the fact that crustaceans are the most commonly farmed aquatic organisms worldwide (FAO 2022).

Most of the size-related studies used computer vision to estimate fish length, from which body mass was, in some cases, calculated from length–weight relationship (Nehemia et al. 2012; Jones, Petrell, and Pauly 1999). However, this approach assumes a constant fish length–weight ratio (isometric growth) and ignores seasonal growth stanzas, which can introduce errors in biomass estimates (Lorenzen 2016). An alternative approach would be to use MV to estimate body mass from changes in body size ratios (Stevenson and Woods 2006), and this an area that merits further investigation given the close relationship between body condition and fish welfare (Gutierrez Rabadan et al. 2021; Rey Planellas and Garcia de Leaniz 2024).

The second most common use of MV in aquaculture was behavioural monitoring (11%), although this mostly addressed the monitoring of feeding activity (Feng et al. 2022; Z. Liu et al. 2014; G. Wang et al. 2021; Yang, Shi, and Wang 2022). To our knowledge, algorithms have not yet been developed to quantify complex individual behaviours necessary for behaviour-based welfare monitoring (Rey Planellas and Garcia de Leaniz 2024), and this is an area where research is also needed. Some studies have recently applied pose estimation (B. Lin et al. 2021; J.-H. Wang et al. 2020) as a first step to characterise behaviours, as used in terrestrial livestock, where behaviours are inferred from the spatial position within an enclosure (Lei et al. 2022; Guo, He, and Chai 2020). In aquaculture, a similar approach could be used in tanks or sea cages enriched with 'furniture', such as hides or designated feeding stations.

The remaining studies used MV for organism detection (10%) or species identification (5%), which is important under polyculture, where different species are reared together and there is a need to monitor their welfare or behaviours separately. Only a handful of publications have applied MV for individual identification (4%). While individual identification might be useful for small-scale studies, it may not be feasible—or even relevant—in large net pens, where tens of thousands of individuals may be present. The difference in visibility between laboratory and commercial conditions is also an important consideration, as poor lighting and increased turbidity may make it more challenging to use MV in farm settings. Most of the studies that used MV for organism identification used pre-existing datasets or pre-existing images (75%) instead of creating their own videos or images. While not all of the images from these datasets were obtained in an aquaculture setting, this approach could still be applied to organisms in aquaculture, especially those in sea cages, as many datasets were taken from the open ocean including Fish4knowledge (Fisher et al. 2016), Deepfish (https://alzayats.github.io/DeepFish/) and IOCAS (Zhu et al. 2022) datasets. However, the extent to which models trained on images of organisms in the wild can be generalised effectively to industrial tank settings is uncertain. In this sense, there is a need for videos and image datasets from aquaculture or aquaculture-like settings that can be used to train algorithms destined for deployment in the industry. This would ease the transition from training to deployment, as there will be a higher similarity between training and testing data sets,

TABLE 1 | Summary of studies using machine vision (MV) in aquaculture that met the systematic review criteria.

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
Abinaya, Susan, and Sidharthan (2022)	Fish	Biomass	YOLOv4 (segment detection), deep learning network	Single camera	Out of water—dead	91.52% accuracy (validation for biomass); 0.941 mAP YOLO, 95.4% CVFs
M. S. Ahmed, Aurpa, and Azad (2022)	Fish—dataset	Disease	CNN combined with SVM	Single camera	Dead	91.42% (without augmentation), 94.12% (with augmentation)
Al Duhayyim et al. (2022)	Fish—dataset	Fish	mask R-CNN (CapsNet Model)	Single camera—in water	In water—alive	Accuracy: blurred: 98%, crowded: 97%, *F* score: blurred: 96%, Crowded: 97%
Al-Jubouri et al. (2017)	Fish	Length		Single camera—out of water	In water—alive	Average estimation error of approximately 1%
Atienza-Vanacloig et al. (2016)	Fish	Individual ID		Single camera—in water	In sea cage, alive	Up to 90% success rate
Banno et al. (2022)	Fish—multiple species	Species and counting (wild fish abundance monitoring)	YOLOv4	Single camera—in water	In water—alive	False positive and false negative rates < 7%
Bekkozhayeva and Cisar (2022)	Fish—multiple species	Individual ID		Single camera	Out of water—alive	SB: ST:100%–91.66%, LT: 100%–40.62% | CC: ST: 100%, LT: 80.64%–29.03%
Böer et al. (2023)	Multiple classes—dataset	Species ID and counting	YOLOv5	Stereo vision—in water	In water—alive	Mean detection accuracy: 92.4%, mAP: 94.8%, F1 score: 93%
Bonofiglio et al. (2022)	Fish	Detection and classification, then abundance estimation	YOLOv5	Single camera—in water	In water—alive	92% Average precision (AP) on 730 test images, and a fivefold cross-validation AP of 93% (±3.7%)
Bravata et al. (2020)	Fish—dataset	Size	DCNN	Single camera—6 in succession	Fed through a slide—alive	Mean percentage errors: 5.5%–7.6%
C. C. Chang et al. (2022)	Fish—multiple species	Species ID	YOLOv4, mask R-CNN	Stereo vision—in water	In tank and sea cage, alive	True positive rate: A (tank): 85%, B (cage): 90%, C (tank): 75%
C.-H. Chang, Weng, et al. (2021)	Fish—multiple species	Length and weight	Faster R-CNN	Stereo vision—in water	In tank and sea cage, alive	Estimated error—3.84%
Cisar et al. (2021)	Fish	Individual ID	CNN	Single camera—outside tank (side)	Both in the tank and out	100% accuracy
Costa et al. (2013)	Fish	Multiple		Single camera	Dead	Regression efficiency ($r = 0.98$), discrimination efficiency for sex and malformation estimation was equal to 82% and 88%

(Continues)

TABLE 1 | (Continued)

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
De Vos et al. (2023)	Echinoderm—multiple species	Dimension measurements		Single camera	Out of water—alive	Mean coefficient of variation: 1.55%
Deng et al. (2022)	Fish—multiple species	Length	ResNeXt50, Keypoints R-CNN	Stereo vision—in water	In tank—alive	Bounding box: mAP: 0.87, key point: mAP: 0.99
Feng et al. (2022)	Fish	Feeding intensity	3D ResNet-GloRe	Single camera—above water	In tank—alive	Accuracy 93%
Gong et al. (2023)	Fish—dataset	Species ID		Single camera	Multiple	Accuracy: 98% (high res), 94% (low res) | F1: 95 (high), 94 (low)
Gupta et al. (2022)	Fish	Wound and lice detection	VGG-19 (based on), CNN (15 layers)	Single camera—in water	In tank—alive	91% (lice), 93% (wounds)
Hao, Yin, and Li (2022)	Fish	Mass		Single camera	Out of water—alive	R^2: 0.991, RMSE: 7.10 g, MAE: 5.36 g, MaxRE: 8.46%
Hong Khai et al. (2022)	Crustaceans	Density	Resnet101, mask R-CNN	Single camera—above water	In tank—alive	Up to 97.5%
Y. Huang and Khabusi (2023)	Fish—dataset	Disease	Multi-layer fusion attention CNN-OSELM network	Single camera—in water	In water—alive	94.28% of accuracy, precision of 92.67%, recall of 92.17% and 92.42%
J. Huang et al. (2022)	Fish	Behaviour	Graph convolution network	Single camera—above water	In tank—alive	Classification accuracy up to 97.3%
Jang et al. (2022)	Fish	Abnormal behaviour	Darknet-53 backbone, YOLOv3	Single camera—above water	In tank—alive	98.10%
Da Silva Oliveira Junior et al. (2021)	Fish	Mass	InceptionV3, ResNet50, VGG16/19, Xception, J48	Single camera	Fed through a slide—alive	Accuracy: J48: 58.2%, ResNet50: 67.08%
Kim, Choe, and Zhang (2023)	Bivalves—multiple species	Parasite	Microsoft Azure Custom Vision	Single cameras in photo booth ×3 angles	Out of water	Oysters: mAP: 71.5, 69.6, 16.5, 5.1% | Scallops: mAP: 43.6, 34.5%
D. Lee et al. (2014)	Echinoderm	Weight		Single camera—outside tank	In tank—alive	RMSE: 1.434 g, R^2: 0.999
W. Li et al. (2023)	Fish—dataset	Counting	MSENet, MCNN	Single camera—above tank	In tank—alive	MAE: 3.33

(Continues)

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
B. Lin et al. (2021)	Fish	Fish pose	Rotated-YOLO 5, R-CenterNet	Single camera—outside tank (side)	In tank—alive	Precision 90.61%, F1 score: 90%
Lines et al. (2001)	Fish	Mass		Stereo vision—in water	In sea cage, alive	Mean error: mass: 18%, linear dimensions < 10%
Z. Liu et al. (2014)	Fish	Feeding		Single camera—above water	In tank—alive	R^2: 0.9195
Lopez-Tejeida et al. (2023)	Fish	Weight		Single camera—above water ans outside tank (side)	In tank—alive	Average accuracy of 92%, true positive rate equal to 95%, false positive rate equal to 12%
Marrable et al. (2023)	Fish—dataset	Length	YOLOv5 small	Single camera—in water	In water—alive	Precision: 77.4%, Recall: 70%, F1: 73.51%
Martinez-de Dios, Serna, and Ollero (2003)	Fish	Weight		Stereo vision—in and above water	In tank—alive	< 4% error above, < 5% in water (weight)
Martínez-Vázquez et al. (2019)	Fish	Biomass	InceptionV4, novel CNN	Single camera—above water	In tank—alive	R^2: 0.9999 CTRL, 0.9997 EXP
Muñoz-Benavent et al. (2018)	Fish	Size		Stereo vision—in water	In sea cage, alive	No significant difference between measurements and ground truth
Muñoz-Benavent et al. (2022)	Fish	Size	YOLOv5, mask R-CNN, faster R-CNN	Stereo vision—in water	In tank—alive	No significant difference between measurements and ground truth
Nian et al. (2020)	Fish—multiple species	Fat	Online sequential extreme learning machine	MRI machine	Out of water—alive	89.13% ± 5.32%, 91.43% ± 6.68% and 93.08% ± 6.57%
Odone, Trucco, and Verri (2001)	Fish	Weight		Single camera—slide	Slide—dead	Absolute percentage error: 3%, Standard deviation: 2%
Pache et al. (2022)	Fish	Biomass	ResNet-152, Xception, Inception, and DenseNet-201, Deep neural networks, deep belief networks, CNN	Single camera—above water	Fed through a slide—alive	DBN: R^2: 0.7

(Continues)

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
Palmer et al. (2022)	Fish	Length	Mask RCNN	Single camera	Dead	Mean average precision = 79.8%, dolphinfish-level precision = 96.06%, dolphinfish-level recall = 90.54%, F1 score = 93.21% and model accuracy = 86.10%
Petrellis (2021)	Fish—dataset	Size	Mask R-CNN (COCO pre-trained)	Pair of cameras	In water—alive	Error: 1.9%–13.2%,
Pinkiewicz, Purser, and Williams (2011)	Fish	Behaviour		Single camera—in water	In sea cage, alive	99.3% accuracy
Puig-Pons et al. (2019)	Fish	Biomass		Stereo vision—in water	In sea cage, alive	No significant difference between measurements and ground truth
Qiao et al. (2019)	Echinoderm—multiple species	Organism		Single camera—in water	In lake farm—alive	Accuracy: 98.55%
Ranjan et al. (2023b)	Fish	Mortality	YOLOv7	Single camera—in water	In tank—alive	Precision: 93.4%, mAP: 0.89
Ranjan et al. (2023a)	Fish	Fish	YOLOv5 (Object detection module), Faster R-CNN	Single camera—in water (four diff cameras)	In tank—alive	Gpro with augmentation: mAP: YOLO: 82.9%, FRCNN: 79.7%
Rico-Díaz et al. (2020)	Fish—multiple species	Fish and weight	Feed-forward ANN	Stereo vision—in water	In tank—alive	Using both methods—accuracy of 74%
Risholm et al. (2022)	Fish—multiple species	Length	DBSAN algorithm	3D camera—in water	In tank and sea cage, alive	'Length estimation errors in the order of 1% of manual-measured fish length'
Saberioon and Císar (2018)	Fish	Mass	ResNet, MRCNN	Single camera—above water	In tank—alive	Highest prediction: RF: R^2: 0.84, RMSE = 0.16
Salhaoui et al. (2020)	Bivalves	Population size		Single camera—in water	In water—alive	Precision: 0.93–0.89, recall: 0.78–0.67, IoU: 0.83–0.68
Setiawan, Hadiyanto, and Widodo (2022)	Crustaceans	Weight	BPNN	Single camera—in water	In tank—alive	RMSE: 0.05, MAE: 0.04, R^2: 0.96
Shi et al. (2022)	Fish	Mass		Stereo vision—in water	In tank—alive	Measurement success rate: orthogonal: 96.3%, $< 45°$: 77.7%, $> 45°$: 67.3%
Silva, Aires, and Rodrigues (2023)	Fish—multiple species	Length		Stereo vision—in water	In water—alive	Error $< 1\%$

(Continues)

TABLE 1 | (Continued)

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
Sun et al. (2018)	Fish—dataset	Species ID	AlexNet, GoogLeNet, OxfordNet (VGG-16), 'RGB-Alex-SVM', Deep CNN, Deep uw-CNN	Single camera—in water	In water—alive	RGB-Alex-SVM: 99.68% precision
Tengtrairat et al. (2022)	Fish	Weight	ResNet backbone, Mask R-CNN	Single camera—in water	In tank—alive	MAE: 42.54 g, R^2: 0.70, average weight error of 30.30 ± 23.09 g
Tillett, Mcfarlane, and Lines (2000)	Fish	Mass		Stereo vision—in water	In tank—alive	Average error: 5%
Tonachella et al. (2022)	Fish	Length, weight	YOLOv4 (for object detection), Resnet101 (CNN used)	Stereo vision—in water	In sea cage, alive	Mean difference: length: 3%, weight: 3.6%
Ubina et al. (2022)	Fish—multiple species	Length	Resnet101, video interpolation CNN, semantic segmentation CNN, MASK R-CNN	Stereo vision—in water	In tank and sea cage, alive	Accuracy: 90% (cage), tank: 92%
Ubina et al. (2023)	Fish—multiple species	Multiple	YOLOv4, Mask-RCNN	Stereo vision—in water	In sea cage, alive	3.44% error
van Essen et al. (2021)	Fish—multiple species	Fish ID, counting	YOLOv3 deep neural network	Single camera	Dead	Weighted counting error of 20%
Viazzi et al. (2015)	Fish	Mass		Single camera	Out of water—alive	Estimated mean relative error was 6% ± 3% and coefficient of determination of 0.99
Wang et al. (2020)	Fish	Abnormal behaviour, posture classification	Faster R-CNN	Single camera—in water	In tank—alive	Faster-rcnn: Accuracy ≈ 92.8 %, F1 score = 0.81, precision ≈ 84%, sensitivity ≈ 80%, and mAP (mean average precision) = 49.80%
G. Wang et al. (2021)	Fish	Behaviour, schooling	FLowNet2, 3D CNN	Single camera—above water	In tank—alive	Average accuracy: 95.79%
Wen et al. (2023)	Multiple classes—dataset	Organism	YOLOv5s-CA	Stereo camera—in water	In water—alive	mAP: 80.9%
Xiao, Li, and Zhao (2023)	Echinoderm—multiple species	Organism	YOLOv5, PANet	Single camera—in water	In water—alive	mAP: 0.90
Xu et al. (2023)	Echinoderm	Disease	DT-YOLOv5	Single camera—above water	In tank—alive	precision: 99.43%, recall: 98.91%, $AP_{50:95}$: 84.89%

(Continues)

TABLE 1 | (Continued)

Author	Taxon	MV use	CNN	Camera type	Organism state	Algorithm performance
Yang, Shi, and Wang (2022)	Fish	Feeding	YOLOv4-Tiny-ECA	Single camera–3 pov (2 side, 1 bottom)	In pond—alive	Precision rate, recall rate, and F1 score angle feeding: 96.23%, 95.92%, 0.96. vertical feeding: 95.89%, 96.44%, 0.96
Yu et al. (2022)	Fish	Weight		Binocular vision—in water	In tank—alive	Accuracy: 94.43%, precision: 90.21%, Recall: 98.54%, F1 score: 94.04%
G. Yu et al. (2023)	Fish—multiple species	Disease	MobileNet3-GELU-YOLOv4 (based on YOLOv4), R-CNN	Single camera	In sea cage and out of water	Accuracy: 98.98%, Recall: 98.65, mAP: 99.64%
. Zhang, Yang, et al. (2020)	Fish	Population size	Multi-column CNN	Single camera—in water	In sea cage, alive	MAE: 4.29, RMSE: 5.57, accuracy: 95.06
Zhang, Li, et al. (2020)	Fish	Population size	BPNN	Single camera—above tank	In tank—alive	Mean absolute error of 0.2985, root mean square error of 0.6105 and a coefficient of determination of 0.9607
Y. Z. Zhang et al. (2021)	Fish—dataset	Fish ID classification	Deep neural network	Single camera—in water	In water—alive	Recognition: 98%
Zhang, Wu, and Bao (2022)	Fish—dataset	Fish detection segmentation	Dual pooling-aggregated Attention Network	Single camera—in water	In water—alive	Mmean IoU: Deepfish: 91.08%, SUIM: 85.39%
L. Zhang et al. (2022)	Crustaceans	Population size	Light-YOLOv4 (YOLOv3 for target detection)	Single camera—above tank	In tank—alive	Mean average precision—93.16%
Zhang et al. (2024)	Fish	Biomass	DL-YOLO (based on YOLOv5n)	Stereo vision—in water	In tank—alive	Single factor model: MRE: 2.87% (between true + estimated weights), no significant difference either I multi factor: length weight MRE: 8.86%, height-weight: 7.41%
. Zhou et al. (2018)	Fish	Behaviour		Single camera—above water	In tank -alive	Accuracy: 98%
Zhou et al. (2023)	Fish	Length		Stereo vision—above tank	In tank—alive	Relative % error: 0.9%
Zhu et al. (2022)	Fish—dataset	Organism	YOLOv4-embedding	Single camera—in water	In water—alive	300 epochs: mAP_{75}: 0.856, precision: 0.86, recall: 0.82

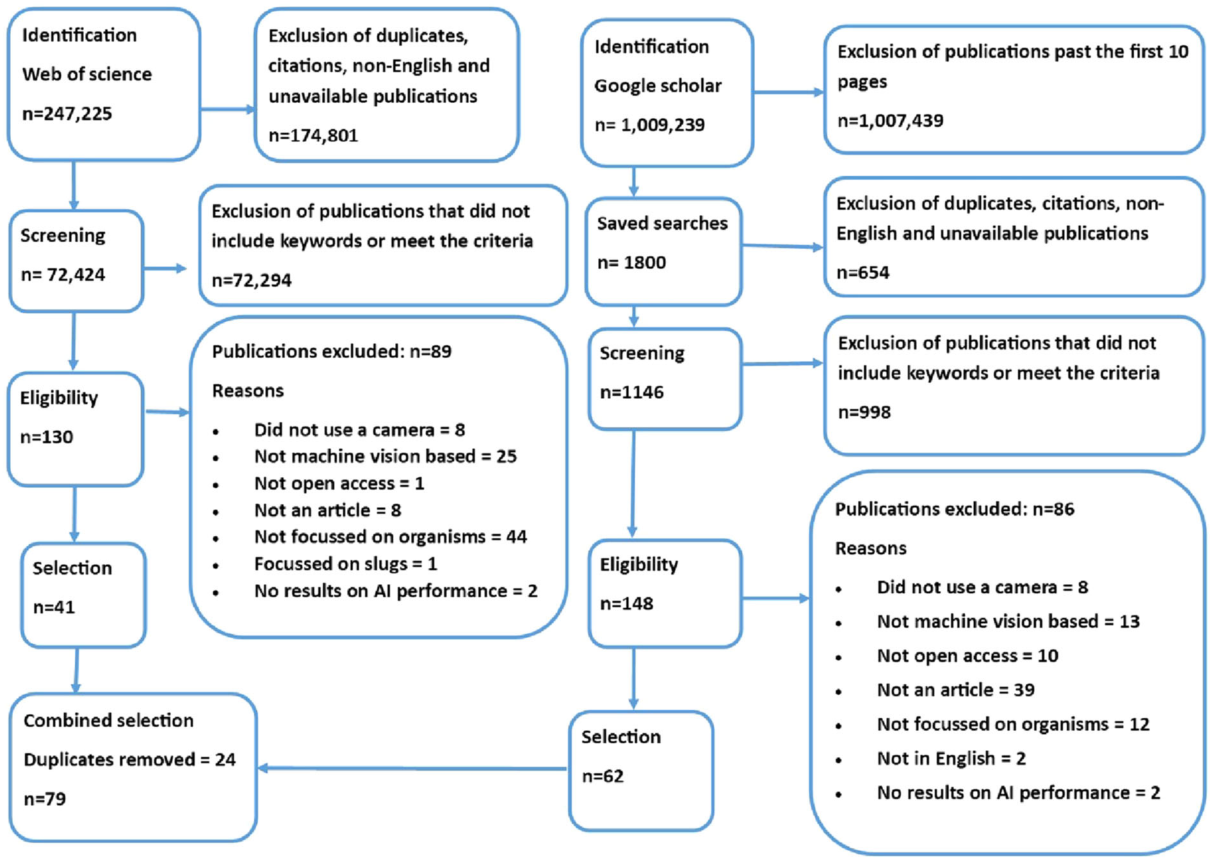

FIGURE 2 | Selection criteria used for the systematic review following the PRISMA protocol.

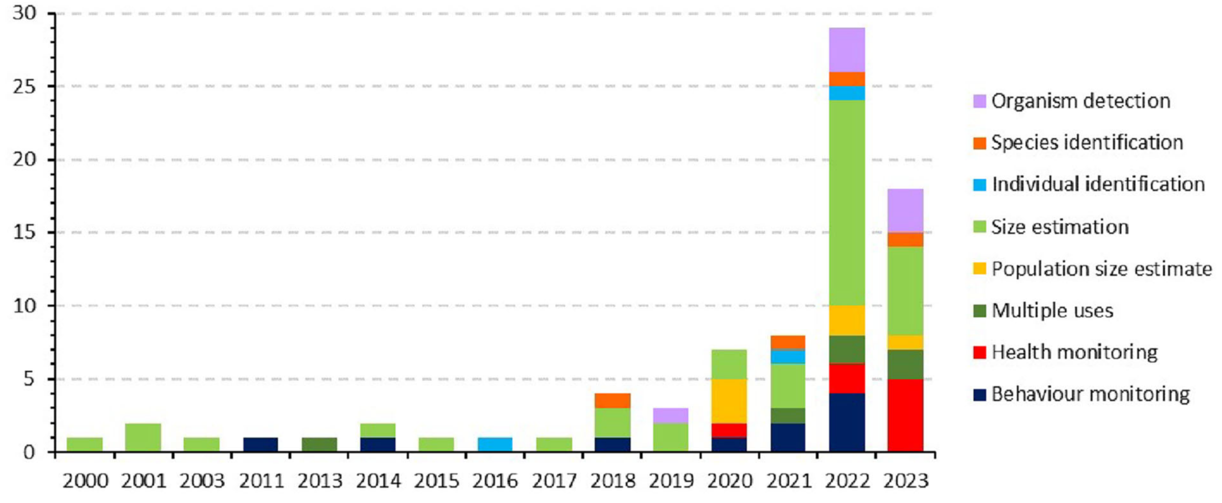

FIGURE 3 | Temporal trend in the use of MV for different tasks in aquaculture ($N = 79$).

minimising the time needed to retrain to new circumstances. Another advantage of using similar training and testing data sets is that it will allow easier comparison of the performance of different algorithms and techniques (D. Li, Wang, et al. 2022).

Health monitoring accounts for 10% of MV studies, with only three studies looking at disease detection (M. S. Ahmed, Aurpa, and Azad 2022; Xu et al. 2023; G. Yu et al. 2023) and only one study used MV to detect sea lice in salmon (Gupta et al. 2022). This is an urgent area of research due to the devastating effects that diseases and parasites have on aquaculture (Lafferty et al. 2015; Costello 2009), the potential for outbreaks to spread to wild populations (Bouwmeester et al. 2021), and the severe impacts on welfare. An early warning system able to detect the onset of disease in real time would be highly beneficial for the rapid isolation or treatment of affected individuals and for minimising disease impacts on welfare.

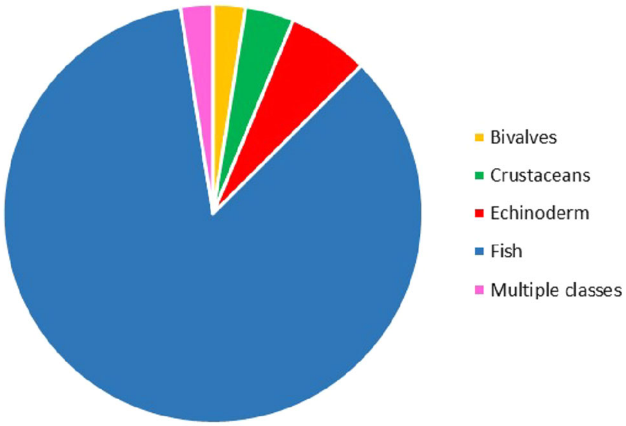

FIGURE 4 | Distribution of MV studies in aquaculture by taxa ($N = 79$).

A few studies used MV to estimate population size (8%). This is also an area in need of research, especially in sea cages, where monitoring of losses due to escapes, predation, or disease is challenging and could indicate poor welfare (Duk et al. 2017). This application would be less useful in closed systems, where escapes are typically not an issue, but there is still a risk of cannibalism, especially in decapod crustaceans (Romano and Zeng 2017), where MV can also be used for larval counting (Hong Khai et al. 2022).

The development of MV approaches that combine different algorithms presents interesting opportunities for monitoring complex welfare-related traits, although currently, only 8% of papers use MV for multiple uses. Two potential applications of a multiple-algorithm approach would be to combine species identification with a body condition or with size estimation in polyculture (e.g., when cleaner fish are used in salmon farming; Powell et al. 2018), or to combine size estimation with feeding activity or health status in monoculture. Combining algorithms that capture different traits may allow the calculation of more meaningful welfare scores and provide a more holistic approach to measuring welfare instead of relying on single measures (Rey Planellas and Garcia de Leaniz 2024).

3.2 | Organisms Monitored Through MV in Aquaculture

The majority of MV studies in aquaculture have focussed on fish (85%), followed by echinoderms (6.3%) and crustaceans (3.8%; Figure 4). The paucity of MV studies on crustaceans represents an important knowledge gap because shrimp are the most widely farmed aquatic organisms in the world (Miao and Wang 2020) and there is increased pressure to monitor welfare in crustaceans (UK Public General Acts 2022).

Some MV studies (21.5%) report monitoring several species simultaneously, suggesting that some algorithms are generic enough to be able to perform the same functions across taxa, which could reduce costs to farms and increase uptake by industry. For example, the same algorithm can be used to estimate body size in multiple species with a similar fusiform body shape with less than 10% error (C.-C. Chang, Wang, et al. 2021; Deng et al. 2022; Risholm et al. 2022; Ubina et al. 2022; Rico-Díaz et al. 2020; Silva, Aires, and Rodrigues 2023). For species with more unique body shapes, such as the round body shape of lumpfish, combining species identification with size estimation in polyculture would ensure that the correct parameters of the length–weight relationship are applied (Gutierrez Rabadan et al. 2021), depending on the species.

3.3 | Possibilities Offered by Publicly Available Image Databases

The use of publicly available image databases, for example, Fish4Knowledge (Fisher et al. 2016), was relatively common (17.7%) in MV applications, particularly for species identification and organism detection. The advantage of using existing image databases is that it can simplify and reduce the time required for obtaining a training dataset, which can be time-consuming, and determines in part algorithm performance (Mikołajczyk and Grochowski 2018; Benos et al. 2021). The Fish4knowledge database has 1 TB of publicly available fish images and has already been used in several MV studies (Y. Z. Zhang et al. 2021; Sun et al. 2018; Al Duhayyim et al. 2022). Although Fish4knowledge currently consists of images of wild fish, a similar dataset could be developed for farmed species for use in aquaculture, reducing in this way the need for data augmentation, that is, the rotation, cropping and colour correction of training images. Data augmentation could also be used to overcome poor visibility in turbid waters (Tengtrairat et al. 2022). The lack of publicly available data is a common problem found across industries that use MV, including medicine, manufacturing and agriculture (Abd Aziz et al. 2020), as it is the need for expert knowledge for image annotation, although the latter can be overcome to some extent through transfer learning and unsupervised training (Smith, Smith, and Hansen 2021).

3.4 | Overview of Hardware

An essential part of the MV system is the camera. Two types of cameras are used most often in MV applications: single cameras and stereoscopic cameras. Stereoscopic vision (used in 24% of studies) is achieved by combining simultaneous images from two cameras or lenses to create a 3D image, like human vision (Chan et al. 2018). Most of the studies that used stereoscopic vision were for size estimation (44% of size estimation studies). Although stereoscopic cameras, such as those used in ReelBiomass (https://www.reeldata.ai/reelbiomass) and BiomassPro (https://www.innovasea.com/aquaculture-intelligence/biomass-estimation/) yield high accuracy in size estimation (typically < 5% error or no different from ground truthing data), they also suffer from some shortcomings, including higher computational costs and a greater risk of camera occlusion (K. Zhou, Meng, and Cheng 2020) which can lead to slow uptake in aquaculture. There is, hence, a need to optimise the use of MV employing single cameras already in use in aquaculture, including feeding cameras routinely employed to monitor feeding behaviour in fish cages (Føre et al. 2018), as these tend to be more affordable and less error-prone than purposely built stereoscopic cameras. There is also potential for cameras to

TABLE 2 | Neural networks and algorithms used in the papers included in the analysis.

Neural network/algorithm	Description	Reference
Convolutional neural network (CNN)	An artificial neural network suited for image recognition tasks	Zhou et al. (2019)
Artificial neural network (ANN)	Computer processing systems inspired by the human brain	Almero et al. (2019)
Support vector machine (SVM)	A supervised learning algorithm used for (often binary) classification	Ahmed, Aurpa, and Azad (2022), Sun et al. (2018), Da Silva Oliveira Junior et al. (2021), Qiao et al. (2019)
Region-based convolutional neural network (RCNN)	Uses a selective search to extract ROIs (regions of interest). These ROIs are then fed into a NN to produce output features. Then it uses SVMs to classify objects found in each ROI	Girshick et al. (2014),Wang et al. (2020), Yu et al. (2023)
Faster RCNN	ROI generation is integrated into the RCNN	Ren et al. (2016), Wang et al. (2020), Chang, Wang, et al. (2021a), Muñoz-Benavent et al. (2022), Ranjan et al. (2023b)
Mask region-based convolutional neural network (Mask RCNN)	RCNN with added instance segmentation	He et al. (2017), Ubina et al. (2022), Ubina et al. (2023), Palmer et al. (2022), Hong Khai et al. (2022), Tengtrairat et al. (2022), Muñoz-Benavent et al. (2022), Petrellis (2021), -Chang et al. (2022)
AlexNET	A deep learning algorithm	Alom et al. (2019), Sun et al. (2018)
Back propagation neural network (BPNN)	A neural network that uses error backpropagation to adjust weights during training, thereby improving performance	Rumelhart, Hinton, and Williams (1986), Setiawan, Hadiyanto, and Widodo (2022), Zhang, Li, et al. (2020)
Density-based spatial clustering of applications with noise algorithm (DBSCAN)	Density-based non-parametric clustering algorithm. Groups closely packed points together	Ester et al. (2018), Risholm et al. (2022), Ubina et al. (2023)
Keypoints R-CNN	Based on the He et al. Mask RCNN 2017 paper	Deng et al. (2022) https://pytorch.org/vision/main/models/keypoint_rcnn.html
Residual networks (ResNet (101 and 50))	A high-performance deep convolutional neural network with good generalisation, suitable for image recognition	He et al. (2016), Hong Khai et al. (2022), Tengtrairat et al. (2022), Feng et al. (2022), Tonachella et al. (2022), Da Silva Oliveira Junior et al. (2021), Pache et al. (2022), Saberioon and Císar (2018), Ubina et al. (2022), Zhang, Wu, and Bao (2022)
Visual Geometry Group (VGG (16 and 19))	A popular deep CNN with numerous layers used for image recognition	Gupta et al. (2022), Sun et al. (2018), Da Silva Oliveira Junior et al. (2021), Petrellis (2021) https://www.robots.ox.ac.uk/~vgg/
Microsoft Azure Custom Vision	Online service allows creation of custom computer vision models	Kim, Choe, and Zhang (2023) https://azure.microsoft.com/en-gb/products/ai-services/ai-custom-vision
You Only Look Once (YOLO v.3-5 and 7)	Object detection algorithm.	Redmon et al. (2016), Jang et al. (2022), Lin et al. (2021), Ranjan et al. (2023a), Wang et al. (2020), Xu et al. (2023), Marrable et al. (2023), Muñoz-Benavent et al. (2022), Tonachella et al. (2022), Abinaya, Susan, and Sidharthan (2022), Zhang et al. (2024), Böer et al. (2023), Yu et al. (2023), Wen et al. (2023), Yang, Shi, and Wang (2022), Zhu et al. (2022), Xiao, Li, and Zhao (2023), Chang et al. (2022), Banno et al. (2022), Bonofiglio et al. (2022), Ubina et al. (2023), Zhang et al. (2022), van Essen et al. (2021)

(Continues)

TABLE 2 | (Continued)

Neural network/algorithm	Description	Reference
FlowNet2	A CNN architecture that learns the concept of optical flow directly from data	Ilg et al. (2017), Wang et al. (2021)
Inception (v.3-4)	Image classification models	Szegedy et al. (2016), Da Silva Oliveira Junior et al. (2021), Martínez-Vázquez et al. (2019), Pache et al. (2022)
MSENet	A multi-scale enhanced network used for image fusion	Li, Li, et al. (2022), Li et al. (2023)
Graph CNN	Neural networks that work with graph structures, capable of learning from the location of nodes in a graph	Danel et al. (2020), Huang et al. (2022)
Dual pooling-aggregated attention network (DPANet)	A framework for semantic segmentation that incorporates two attention modules	Zhang, Wu, and Bao (2022)
Multi-column CNN	A number of columns are trained on inputs pre-processed in different ways and the final predictions are obtained by averaging individual predictions of all these columns	Zhang et al. (2016), Zhang, Li, et al. (2020)
Principal component analysis and support vector machine (PCA-SVM)	A machine learning pipeline between PCA and SVM	Qiao et al. (2019)
Semantic segmentation CNN	Semantic segmentation is where every pixel in an image is assigned a class label, for example, 'background'	Ubina et al. (2022)
Feed-forward ANN	The data in the network only goes in one direction—forward through the network	Rico-Díaz et al. (2020)
Deep neural network	An ANN with many layers between input and output layers	Zhang et al. (2021)
Principal component analysis (PCA)	Used for dimensionality reduction in machine learning—reduce dataset size while maintaining patterns	Greenacre et al. (2022), Qiao et al. (2019), Tillett, Mcfarlane, and Lines (2000), Ubina et al. (2023)

be used in conjunction with acoustic systems (Puig-Pons et al. 2019). Acoustic telemetry has been used to track the behaviour of cleaner fish in salmon cages (Leclercq et al. 2018) and could complement MV when there is poor visibility due to turbidity, poor lighting, reflection or overlapping of fish.

Roughly half of the MV studies (54%) had cameras positioned outside the water, which makes them easier to deploy and operate and can facilitate the monitoring of changes in behaviour (Feng et al. 2022; Jang et al. 2022; G. Wang et al. 2021). However, recording from above can cause issues with light reflections and glare that may affect organism detection, something less likely to occur with underwater cameras. To overcome this problem, the detection of anomalous values and filtering can be used (Z. Liu et al. 2014).

When underwater cameras are used, these are usually pointed towards the surface as this tends to result in better-defined silhouettes against a lighter background (Atienza-Vanacloig et al. 2016) and can be used for size estimation (Muñoz-Benavent et al. 2018; Muñoz-Benavent et al. 2022). However, the camera system that can be used will also depend on the type and stage of the organism being farmed, the aquaculture system, and the welfare metrics that want to be monitored. For example, in sea cages, all studies examined used submerged cameras, whereas there is more flexibility for camera setups in tanks.

The vast majority of MV studies monitored live organisms kept in the water (76.3%), indicating that there is potential for welfare to be monitored non-intrusively, avoiding handling or air exposure. Studies that used MV with organisms out of the water (Bekkozhayeva and Cisar 2022; Nian et al. 2020; De Vos et al. 2023; Hao, Yin, and Li 2022) are more likely to cause stress and to some extent defeat the purpose of non-invasive measures, but can be useful for size estimation of samples obtained for quality control or other monitoring purposes (Abinaya, Susan, and Sidharthan 2022; Odone, Trucco, and Verri 2001). There does not appear to be much difference in the accuracy of size estimation of live and dead organisms, suggesting that MV can also be useful for biomass estimation.

TABLE 3 | Common techniques and software used in the studies included in the analysis.

Technique/software	Description	Reference
Haar classifier	Object detection algorithm that uses Haar features—the changes in intensity between adjacent rectangles of pixels	Wilson and Fernandez (2006), Lopez-Tejeida et al. (2023)
Euclidean distance matrix analysis	The length of a straight line between two points	Cisar et al. (2021), Muñoz-Benavent et al. (2018), Deng et al. (2022), Pache et al. (2022), Petrellis (2021), Bonofiglio et al. (2022), Costa et al. (2013)
Feature pyramid networks (FPN)	Used to detect objects at different scales	Lin et al. (2017), Xu et al. (2023), Wen et al. (2023), Al Duhayyim et al. (2022), Yang, Shi, and Wang (2022), Zhu et al. (2022)
Gaussian mixture model	Clustering algorithm—probability based. Used to group data points together using a 'soft clustering' technique	Zhou et al. (2023), Saberioon and Císar (2018), Böer et al. (2023), Al Duhayyim et al. (2022),Chang et al. (2022)
K-means	Clustering algorithm—distance based. Tries to group the closest points into a cluster based on the number of groups wanted. The data are assigned to a group based on the closest centroid, the centroids update until the error is minimised and they no longer change location	Ahmed, Seraj, and Islam (2020), Muñoz-Benavent et al. (2022)
Mask	Binary images that highlight certain regions or objects in an image	
Internet of things (IOT)	A network of devices and sensors connected through the cloud	Petrellis (2021),Chang et al. (2022), Viazzi et al. (2015), Ubina et al. (2023)
Intersection over union (IoU)	Used to evaluate the performance of object detection algorithms by comparing the ground truth bounding box and the predicted bounding box	Xiao, Li, and Zhao (2023), Deng et al. (2022), Böer et al. (2023)
Region of Interest (ROI)	The region of an image that is used for detailed analysis—often shown by a bounding box	Bekkozhayeva and Cisar (2022), Hong Khai et al. (2022), Lopez-Tejeida et al. (2023), Zhang et al. (2021), Zhou et al. (2023), Setiawan, Hadiyanto, and Widodo (2022), Cisar et al. (2021), Abinaya, Susan, and Sidharthan (2022), Pache et al. (2022), Al Duhayyim et al. (2022), Odone, Trucco, and Verri (2001), Rico-Díaz et al. (2020)
Background subtraction	Used to detect moving objects by looking at the difference between the current frame and a reference frame. Often used to create a foreground mask	Piccardi (2004), Atienza-Vanacloig et al. (2016), Zhou et al. (2018), Al Duhayyim et al. (2022), Rico-Díaz et al. (2020), Huang and Khabusi (2023)
Zhang-Suen refinement algorithm	A thinning algorithm that reduces patterns to a 'skeleton'	Zhang and Suen (1984), Zhou et al. (2023)
Thresholding	Used to separate out a section of images into the object of interest and the background—several types (binary, local, adaptive, method)	Sahoo, Soltani, and Wong (1988), Setiawan, Hadiyanto, and Widodo (2022), Atienza-Vanacloig et al. (2016), Cisar et al. (2021), Muñoz-Benavent et al. (2018), Puig-Pons et al. (2019), Pinkiewicz, Purser, and Williams (2011), Saberioon and Císar (2018), Lines et al. (2001)

(Continues)

TABLE 3 | (Continued)

Technique/software	Description	Reference
Segmentation	Dividing an image into different segments—several types (3D, instance, image, blob, semantic)	Ghosh et al. (2019), Zhang et al. (2021), Muñoz-Benavent et al. (2018), Muñoz-Benavent et al. (2022), Puig-Pons et al. (2019), Martinez-de Dios, Serna, and Ollero (2003), Pinkiewicz, Purser, and Williams (2011), Shi et al. (2022), Ubina et al. (2022), Wang et al. (2021), Yu et al. (2022), Chang et al. (2022), Huang and Khabusi (2023), Ubina et al. (2023), Viazzi et al. (2015), Palmer et al. (2022)
Kalman filter	An algorithm that can predict future positions based on current position	Pinkiewicz, Purser, and Williams (2011), van Essen et al. (2021), Welch (2021)
Data/image augmentation	Artificial generation of new data using existing data. In machine vision this includes applying image transformations including: cropping, rotation, mirroring, brightening, colour changes.	Ahmed, Aurpa, and Azad (2022), Gupta et al. (2022), Sun et al. (2018), Pache et al. (2022), Bravata et al. (2020), Gong et al. (2023), Yu et al. (2023), Yang, Shi, and Wang (2022), Ranjan et al. (2023a), Huang et al. (2022), van Essen et al. (2021)
Keras	API used to build neural networks—uses Python	Pache et al. (2022), Bravata et al. (2020), Petrellis (2021), Zhang, Li, et al. (2020) https://keras.io/
Checkerboard/chessboard calibration	The use of a checkerboard or a chessboard to calibrate a stereo vision camera	Saberioon and Císar (2018), Böer et al. (2023), Chang et al. (2022), Tonachella et al. (2022)
Nearest neighbour methods	Finds the closest object from the training set to the object being classified in N-dimensional space. These objects are likely the same class as they are close to each other. Several methods: k, classification, interpolation	Nisbet, Miner, and Yale (2009), Setiawan, Hadiyanto, and Widodo (2022), Abinaya, Susan, and Sidharthan (2022), Pinkiewicz, Purser, and Williams (2011), Saberioon and Císar (2018), Xiao, Li, and Zhao (2023)
Edge detection	Used to identify the edges of an object in an image	Sharifi, Fathy, and Mahmoudi (2002), Setiawan, Hadiyanto, and Widodo (2022), Muñoz-Benavent et al. (2018), Puig-Pons et al. (2019), Pinkiewicz, Purser, and Williams (2011), Petrellis (2021)
TensorFlow	Open-source software library for machine learning and AI	Hong Khai et al. (2022), Bravata et al. (2020), Petrellis (2021) https://www.tensorflow.org/
Pytorch	Machine learning library	Tonachella et al. (2022), Deng et al. (2022), Wang et al. (2021), Yu et al. (2023) https://pytorch.org/

3.5 | Overview of Software and Technological Readiness Level

Currently, one of the main limitations on the use of MV in aquaculture is that almost half of the studies (45%) are based on observations from experimental tanks (Technological Readiness Levels, TRL 3–4), which may differ widely from commercial rearing conditions. For example, some studies used single fish housed in tanks (Lopez-Tejeida et al. 2023; Al-Jubouri et al. 2017) to develop algorithms that may not work well under commercial conditions, where there may be tens of thousands of individuals, making detection of overlapping images challenging. Similar challenges occur in the application of MV in agriculture and terrestrial animal farming, and solutions developed to facilitate the identification of occluded individuals in livestock farming (E. Huang et al. 2021) could also be applied to aquaculture. Alternatively, some researchers mitigate this problem by analysing the group of animals as a whole rather than trying to track individuals (Dawkins et al. 2021).

The most commonly used technique for MV is convolutional neural networks (CNN) using the YOLO software (28%), an algorithm used for object detection (Jiang et al. 2021), and more recently also for pose detection (https://docs.ultralytics.com/tasks/pose/) which can help identify and monitor behaviours. Some studies combined YOLO (often as an object detection module) with different CNNs or other ML techniques (Tonachella et al. 2022; Ranjan et al. 2023a). Other popular software for MV includes ResNet (K. He et al. 2016) (used in 11.4% of studies), which is useful for both industry and research applications.

In addition to CNN software, non-CNN approaches also exist, including support vector machine (SVM) and deep learning frameworks such as single shot detectors and faster-RCNNs (Mohanty, Balasundaram, and Shaik 2022) that can deal with low-light or high-density conditions. Many of these algorithms benefit from multi-frame tracking, where the identity of individual fish can be tracked over multiple frames based on their previous position. This can be used to estimate swimming velocity and movement patterns, which are useful for behavioural welfare monitoring. Identification of individuals based on melanophore (Garcia de Leaniz et al. 1994) or coating patterns (Andrew et al. 2021) may be possible in some species under some conditions. To overcome the problem of losing track of individuals that may look similar, motion estimation using spatial–temporal context (i.e., momentum) and object-level warping loss have proved useful in biomedicine applications (Hayashida, Nishimura, and Bise 2022) and the same approach could be used in aquaculture (S. Liu et al. 2024). Several other publicly available network architectures are shown in Tables 2 and 3.

4 | Conclusion

The use of MV in aquaculture has increased rapidly over the last few years and will likely continue to increase due to consumer demand for ethically produced seafood and the advent of precision aquaculture. The most common application of MV in aquaculture has so far been size estimation, which is an important production trait for farmers, but can also be used to monitor growth and serve as a welfare indicator. However, there is a paucity of studies using MV to monitor other aspects of welfare, such as health conditions, parasites and disease, which are major problems in aquaculture that need to be addressed. Real-time behavioural monitoring is another area where we anticipate MV will be used more, as it can serve as an early warning system before welfare is seriously compromised. Our systematic review has also highlighted the need for more research on taxa other than fish, especially crustaceans, which are widely farmed. But perhaps the greatest challenge for the application of MV for welfare monitoring in aquaculture is the paucity of studies under commercially relevant conditions, characterised by poor visibility and high densities. Such studies are necessary to advance the current low TRL. In this sense, the availability of publicly available image datasets, the recent development of CNN architectures (like YOLO and ResNet), and the possibility of using existing feeding-monitoring cameras should facilitate the uptake of MV for welfare monitoring in the aquaculture industry. To overcome current limitations and increase the TRL of MV in aquaculture, several recommendations can be made. First, we recommend that algorithms be developed in commercial settings, with a focus on dealing with sub-optimal visibility and high densities, perhaps using image enhancement or other deep learning methods. Second, we recommend the development of multifunctional systems, where multiple welfare metrics can be monitored by the same system, which may make them more economically viable and increase uptake by the aquaculture industry. Finally, the costs, maintenance, and training requirements for workers using MV should also be considered; some of these costs may be reduced if algorithms are trained to work with camera surveillance equipment already in use or if multifunctional systems are employed (Kumar, Singh, and Bhamu 2022).

Author Contributions

Amy Fitzgerald: methodology, data curation, investigation, formal analysis, writing–original draft, visualization. **Christos C. Ioannou**: supervision, writing–review and editing. **Sofia Consuegra**: supervision, writing–review and editing, funding acquisition, conceptualization. **Andrew Dowsey**: writing–review and editing, supervision. **Carlos Garcia de Leaniz**: supervision, writing–review and editing, conceptualization, funding acquisition.

Acknowledgements

Funding for this study was provided by a PhD scholarship to AF by Visifish and Swansea University, and the IGNITION Horizon Europe project (Grant No 101084651). SC was partially funded by a Royal Society Industry Fellowship Ref: IF\R1\231030.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

This review did not generate any data. All the references used in the review are listed in the reference list.

Peer Review

The peer review history for this article is available at https://publons.com/publon/10.1002/aff2.70036.

References

Abd Aziz, N. S. N., S. Mohd Daud, R. A. Dziyauddin, M. Z. Adam, and A. Azizan. 2020. "A Review on Computer Vision Technology for Monitoring Poultry Farm—Application, Hardware, and Software." *IEEE Access* 9: 12431–12445.

Abdel-Tawwab, M., M N. Monier, S. H. Hoseinifar, and C. Faggio. 2019. "Fish Response to Hypoxia Stress: Growth, Physiological, and Immunological Biomarkers." *Fish Physiology and Biochemistry* 45, no. 3: 997–1013.

Abinaya, N. S., D. Susan, and R. K. Sidharthan. 2022. "Deep Learning-Based Segmental Analysis of Fish for Biomass Estimation in an Occulted Environment." *Computers and Electronics in Agriculture* 197: 106985.

Abu Talib, M., S. Majzoub, Q. Nasir, and D. Jamal. 2021. "A Systematic Literature Review on Hardware Implementation of Artificial Intelligence Algorithms." *Journal of Supercomputing* 77, no. 2: 1897–1938.

Ahmed, M., R. Seraj, and S. M. S. Islam. 2020. "The k-means Algorithm: A Comprehensive Survey and Performance Evaluation." *Electronics* 9: 1295.

Ahmed, M. S, T. T. Aurpa, and M. A. K. Azad. 2022. "Fish Disease Detection Using Image Based Machine Learning Technique in Aquaculture." *Journal of King Saud University-Computer and Information Sciences* 34, no. 8: 5170–5182.

Al Duhayyim, M., H. Mesfer Alshahrani, F. N Al-Wesabi, M. Alamgeer, A. Mustafa Hilal, and M. Ahmed Hamza. 2022. "Intelligent Deep Learning Based Automated Fish Detection Model for UWSN." *Computers Materials & Continua* 70, no. 3: 5871–5887.

Al-Jubouri, Q., W. Al-Nuaimy, M. Al-Taee, and I. Young. 2017. "An Automated Vision System for Measurement of Zebrafish Length Using Low-Cost Orthogonal Web Cameras." *Aquacultural Engineering* 78: 155–162.

Almero, V. J., R. Concepcion, M. Rosales, R. R. Vicerra, A. Bandala, and E. Dadios. 2019. "An Aquaculture-Based Binary Classifier for Fish Detection Using Multilayer Artificial Neural Network." In *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*. IEEE, 1–5.

Alom, M. Z., T. M. Taha, C. Yakopcic, et al. 2019. "A state-of-the-art survey on deep learning theory and architectures." *Electronics* 8: 292.

Andrew, W., J. Gao, S. Mullan, N. Campbell, A W. Dowsey, and T. Burghardt. 2021. "Visual Identification of Individual Holstein-Friesian Cattle Via Deep Metric Learning." *Computers and Electronics in Agriculture* 185: 106133.

Antonucci, F., and C. Costa. 2020. "Precision Aquaculture: A Short Review on Engineering Innovations." *Aquaculture International* 28, no. 1: 41–57.

Arends, R., J. Mancera, J. Munoz, S. Wendelaar Bonga, and G. Flik. 1999. "The Stress Response of the gilthead Sea Bream (*Sparus aurata* L.) to Air Exposure and Confinement." *Journal of Endocrinology* 163, no. 1: 149–157.

Ashraf Rather, M., I. Ahmad, A. Shah, et al. 2024. "Exploring Opportunities of Artificial Intelligence in Aquaculture to Meet Increasing Food Demand." *Food Chemistry: X* 22: 101309.

Atienza-Vanacloig, V., G. Andreu-García, F. López-García, J M. Valiente-González, and V. Puig-Pons. 2016. "Vision-Based Discrimination of Tuna Individuals in Grow-Out Cages Through a Fish Bending Model." *Computers and Electronics in Agriculture* 130: 142–150.

Bacher, K. 2015. "Perceptions and Misconceptions of Aquaculture: A Global Overview." *GLOBEFISH Research Programme* 120: 1–35.

Badue, C., R. Guidolini, R. V. Carneiro, et al. 2021. "Self-Driving Cars: A Survey." *Expert Systems With Applications* 165: 113816.

Banno, K., H. Kaland, A. Crescitelli, S. Tuene, G. Aas, and L. Gansel. 2022. "A Novel Approach for Wild Fish Monitoring at Aquaculture Sites: Wild Fish Presence Analysis Using Computer Vision." *Aquaculture Environment Interactions* 14: 97–112.

Barbedo, J. G. A. 2022. "A Review on the Use of Computer Vision and Artificial Intelligence for Fish Recognition, Monitoring, and Management." *Fishes* 7, no. 6: 335.

Barreto, M. O., S. Rey Planellas, Y. Yang, C. Phillips, and K. Descovich. 2022. "Emerging Indicators of Fish Welfare in Aquaculture." *Reviews in Aquaculture* 14, no. 1: 343–361.

Barton, B. A., C. Schreck, and L. Barton. 1987. "Effects of Chronic Cortisol Administration and Daily Acute Stress on Growth, Physiological Conditions, and Stress Responses in Juvenile Rainbow-Trout." *Diseases of Aquatic Organisms* 2, no. 3: 173–185.

Bekkozhayeva, D., and P. Cisar. 2022. "Image-Based Automatic Individual Identification of Fish Without Obvious Patterns on the Body (Scale Pattern)." *Applied Sciences* 12, no. 11: 5401.

Benos, L., A C. Tagarakis, G. Dolias, R. Berruto, D. Kateris, and D. Bochtis. 2021. "Machine Learning in Agriculture: A Comprehensive Updated Review." *Sensors* 21, no. 11: 3758.

Birch, J., C. Burn, A. Schnell, H. Browning, and A. Crump. 2021. *Review of the Evidence of Sentience in Cephalopod Molluscs and Decapod Crustaceans*. London: The London School of Economics and Political Science.

Bishop, C. M. 1994. "Neural Networks and Their Applications." *Review of Scientific Instruments* 65, no. 6: 1803–1832.

Böer, G., J. P. Gröger, S. Badri-Höher, et al. 2023. "A Deep-Learning Based Pipeline for Estimating the Abundance and Size of Aquatic Organisms in an Unconstrained Underwater Environment From Continuously Captured Stereo Video." *Sensors* 23, no. 6: 3311.

Bonofiglio, F., F. C. De Leo, C. Yee, D. Chatzievangelou, J. Aguzzi, and S. Marini. 2022. "Machine Learning Applied to Big Data From Marine Cabled Observatories: A Case Study of Sablefish Monitoring in the NE Pacific." *Frontiers in Marine Science* 9: 842946.

Bouwmeester, M. M., M. A Goedknegt, R. Poulin, and D W. Thieltges. 2021. "Collateral Diseases: Aquaculture Impacts on Wildlife Infections." *Journal of Applied Ecology* 58, no. 3: 453–464.

Bravata, N., D. Kelly, J. Eickholt, J. Bryan, S. Miehls, and D. Zielinski. 2020. "Applications of Deep Convolutional Neural Networks to Predict Length, Circumference, and Weight From Mostly Dewatered Images of Fish." *Ecology and Evolution* 10, no. 17: 9313–9325.

Browman, H. I., S. J. Cooke, I. G. Cowx, et al. 2019. "Welfare of Aquatic Animals: Where Things Are, Where They Are Going, and What It Means for Research, Aquaculture, Recreational Angling, and Commercial Fishing." *ICES Journal of Marine Science* 76, no. 1: 82–92.

Chan, B., K. H. Lim, L. Gopal, A. A. Gopalai, and D. Gouwanda. 2018. "Stereo Vision Human Motion Detection and Tracking in Uncontrolled Environment." *Telkomnika (Telecommunication Computing Electronics and Control)* 16, no. 3: 955–964.

Chang, C. C., N. A. Ubina, S. C. Cheng, H. Y. Lan, K. C. Chen, and C. C. Huang. 2022. "A Two-Mode Underwater Smart Sensor Object for Precision Aquaculture Based on AIoT Technology." *Sensors* 22, no. 19: 7603.

Chang, C.-C., J.-H. Wang, J.-L. Wu, et al. 2021. "Applying Artificial Intelligence (AI) Techniques to Implement a Practical Smart Cage Aquaculture Management System." *Journal of Medical and Biological Engineering* 41, no. 5: 652–658.

Chang, C.-H., J.-S. Weng, P.-S. Chiu, W.-C. Lien, and K. Chiu. 2021. "Artificial Intelligence–Based Image Recognition for Measuring the Size of Grouper in Mariculture." *Journal of the Fisheries Society of Taiwan* 48, no. 4: 227–237.

Cisar, P., D. Bekkozhayeva, O. Movchan, M. Saberioon, and R. Schraml. 2021. "Computer Vision Based Individual Fish Identification Using Skin Dot Pattern." *Scientific Reports* 11, no. 1: 16904.

Cook, K V., R J. Lennox, S G. Hinch, and S J. Cooke. 2015. "Fish out of Water: How Much Air Is Too Much?" *Fisheries* 40, no. 9: 452–461.

Costa, C., F. Antonucci, C. Boglione, P. Menesatti, M. Vandeputte, and B. Chatain. 2013. "Automated Sorting for Size, Sex and Skeletal Anomalies of Cultured Seabass Using External Shape Analysis." *Aquacultural Engineering* 52: 58–64.

Costello, M. J. 2009. "The Global Economic Cost of Sea Lice to the Salmonid Farming Industry." *Journal of Fish Diseases* 32: 115–118.

Council of Europe. 2006. Standing Committee of the European Convention for the Protection of Animals Kept for Farming Purposes (T-AP): Recommendation Concerning Farmed Fish, Adopted by the Standing Committee on 5 December 2005, entered into force on 5 June 2006. In: COUNCIL OF EUROPE.

Danel, T., P. Spurek, J. Tabor, et al. 2020. "Spatial Graph Convolutional Networks." In *Neural Information Processing*, edited by H. Yang, K. Pasupa, A. C. S. Leung, et al. Cham: Springer International Publishing, 668–675.

Da Silva Oliveira Junior, A., D. A. Sant'ana, M. Carneiro Brito Pache, et al. 2021. "Fingerlings Mass Estimation: A Comparison Between Deep and Shallow Learning Algorithms." *Smart Agricultural Technology* 1: 100020.

Dawkins, M. S., L. Wang, S A. Ellwood, S J. Roberts, and S G. Gebhardt-Henrich. 2021. "Optical Flow, Behaviour and Broiler Chicken Welfare in the UK and Switzerland." *Applied Animal Behaviour Science* 234: 105180.

Deng, Y., H. Tan, M. Tong, D. Zhou, Y. Li, and M. Zhu. 2022. "An Automatic Recognition Method for Fish Species and Length Using an Underwater Stereo Vision System." *Fishes* 7, no. 6: 326.

De Vos, B. C., M. D. Cyrus, B. M. Macey, T. Batik, and J. J. Bolton. 2023. "Combining Computer Vision and Standardised Protocols for Improved Measurement of Live Sea Urchins for Research and Industry." *Aquaculture, Fish and Fisheries* 3, no. 6: 507–517.

Duk, K., J. Pajdak, E. Terech-Majewska, and J. Szarek. 2017. "Intracohort Cannibalism and Methods for Its Mitigation in Cultured Freshwater Fish." *Reviews in Fish Biology and Fisheries* 27, no. 1: 193–208.

Ester, M., H. Kriegel, J. Sander, and X. Xu. 2018. "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases With Noise." In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*. 226–231. Association for the Advancement of Artificial Intelligence.

FAO. 2022. The State of World Fisheries and Aquaculture 2022. Rome, Italy: Food and Agriculture Organization of the United Nations.

Feng, S., X. Yang, Y. Liu, et al. 2022. "Fish Feeding Intensity Quantification Using Machine Vision and a Lightweight 3D ResNet-GloRe Network." *Aquacultural Engineering* 98: 102244.

Fernandes, A. F. A., J. R. R. Dórea, and G. J. D. M. Rosa. 2020. "Image analysis and computer vision applications in animal sciences: an overview." *Frontiers in Veterinary Science* 7: 551269.

Fisher, R. B., K.-T. Shao, and Y.-H. Chen-Burger. 2016. "Overview of the Fish4Knowledge project." In *Fish4Knowledge: Collecting and Analyzing Massive Coral Reef Fish Video Data*, edited by R. Fisher, Y. H. Chen-Burger, D. Giordano, L. Hardman, and F. P. Lin, 1–17. Cham: Springer.

Føre, M., K. Frank, T. Norton, et al. 2018. "Precision Fish Farming: A New Framework to Improve Production in Aquaculture." *Biosystems Engineering* 173: 176–193.

Garcia de Leaniz, C., N. Fraser, V. Mikheev, and F. Huntingford. 1994. "Individual Recognition of Juvenile Salmonids Using Melanophore Patterns." *Journal of Fish Biology* 45, no. 3: 417–422.

Ghosh, S., N. Das, I. Das, and U. Maulik. 2019. "Understanding Deep Learning Techniques for Image Segmentation." *ACM Computing Surveys* 52, no. 4: 73.

Girshick, R., J. Donahue, T. Darrell, and J. Malik. 2014. "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 580–587.

Gong, B., K. Dai, J. Shao, L. Jing, and Y. Chen. 2023. "Fish-TViT: A Novel Fish Species Classification Method in Multi Water Areas Based on Transfer Learning and Vision Transformer." *Heliyon* 9, no. 6: e16761.

Greenacre, M., P J. F. Groenen, T. Hastie, A. I. D'enza, A. Markos, and E. Tuzhilina. 2022. "Principal Component Analysis." *Nature Reviews Methods Primers* 2, no. 1: 100.

Guo, Y., D. He, and L. Chai. 2020. "A Machine Vision-Based Method for Monitoring Scene-Interactive Behaviors of Dairy Calf." *Animals* 10, no. 2: 190.

Gupta, A., E. Bringsdal, K. M. Knausgård, and M. Goodwin. 2022. "Accurate Wound and Lice Detection in Atlantic Salmon Fish Using a Convolutional Neural Network." *Fishes* 7, no. 6: 345.

Gutierrez Rabadan, C., C. Spreadbury, S. Consuegra, and C. Garcia de Leaniz. 2021. "Development, Validation and Testing of an Operational Welfare Score Index for Farmed Lumpfish *Cyclopterus lumpus* L." *Aquaculture* 531: 735777.

Hao, Y., H. Yin, and D. Li. 2022. "A Novel Method of Fish Tail Fin Removal for Mass Estimation Using Computer Vision." *Computers and Electronics in Agriculture* 193: 106601.

Hayashida, J., K. Nishimura, and R. Bise. 2022. "Consistent Cell Tracking in Multi-frames With Spatio-Temporal Context by Object-Level Warping Loss." In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 1727–1736.

He, K., G. Gkioxari, P. Dollar, and R. Girshick. 2017. "Mask R-CNN." In *Proceedings of the IEEE International Conference on Computer Vision*, 2961–2969.

He, K., X. Zhang, S. Ren, and J. Sun. 2016. "Deep Residual Learning for Image Recognition." In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Seattle, WA, 770–778.

He, W., T. Liu, Y. Han, et al. 2022. "A Review: The Detection of Cancer Cells in Histopathology Based on Machine Vision." *Computers in Biology and Medicine* 146: 105636.

Hong Khai, T., S. N. H. S. Abdullah, M. K. Hasan, and A. Tarmizi. 2022. "Underwater Fish Detection and Counting Using Mask Regional Convolutional Neural Network." *Water* 14, no. 2: 222.

Huang, E., A. Mao, H. Gan, et al. 2021. "Center Clustering Network Improves Piglet Counting Under Occlusion." *Computers and Electronics in Agriculture* 189: 106417.

Huang, J., X. Yu, X. Chen, D. An, Y. Zhou, and Y. Wei. 2022. "Recognizing Fish Behavior in Aquaculture With Graph Convolutional Network." *Aquacultural Engineering* 98: 102246.

Huang, Y. P., and S. P. Khabusi. 2023. "A CNN-OSELM Multi-Layer Fusion Network With Attention Mechanism for Fish Disease Recognition in Aquaculture." *IEEE Access* 11: 58729–58744.

Ilg, E., N. Mayer, T. Saikia, M. Keuper, A. Dosovitskiy, and T. Brox. 2017. "FlowNet 2.0: Evolution of Optical Flow Estimation With Deep Networks." In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1647–1655.

Jang, J.-C., Y.-R. Kim, S. Bak, S.-W. Jang, and J.-M. Kim. 2022. "Abnormal Behaviour in Rock Bream (*Oplegnathus fasciatus*) Detected Using Deep Learning-based Image Analysis." *Fisheries and Aquatic Sciences* 25, no. 3: 151–157.

Janiesch, C., P. Zschech, and K. Heinrich. 2021. "Machine Learning and Deep Learning." *Electronic Markets* 31, no. 3: 685–695.

Jiang, P., D. Ergu, F. Liu, Y. Cai, and B. Ma. 2021. "A Review of Yolo Algorithm Developments." In *8th International Conference on Information Technology and Quantitative Management (ITQM)—Developing Global Digital Economy After COVID-19*. Chengdu, China, 1066–1073.

Jones, R. E., R. J. Petrell, and D. Pauly. 1999. "Using Modified Length-Weight Relationships to Assess the Condition of Fish." *Aquacultural Engineering* 20, no. 4: 261–276.

Jordan, M. I., and T. M. Mitchell. 2015. "Machine Learning: Trends, Perspectives, and Prospects." *Science* 349, no. 6245: 255–260.

Kim, D., S. Choe, and S.-U. Zhang. 2023. "Recognition of Adherent Polychaetes on Oysters and Scallops Using Microsoft Azure Custom Vision." *Electronic Research Archive* 31, no. 3: 1691–1709.

Korus, J., R. Cordero, R. Pasula, and S. Reddy. 2024. *The Power of Data Science and How It Is Transforming Aquaculture*. p. 17. Boston, USA: Innovasea.

Kumar, P., D. Singh, and J. Bhamu. 2022. "Machine Vision in Industry 4.0. Applications, Challenges and Future Directions." In *Machine Vision for Industry 4.0. Applications and Case Studies*, edited by R. Raut, S.-D. Krit and P. Chatterjee, 22. Boca Raton: CRC Press.

Lafferty, K. D., C. D Harvell, J M. Conrad, et al. 2015. "Infectious Diseases Affect Marine Fisheries and Aquaculture Economics." *Annual Review of Marine Science* 7, no. 1: 471–496.

Leclercq, E., B. Zerafa, A J. Brooker, A. Davie, and H. Migaud. 2018. "Application of Passive-Acoustic Telemetry to Explore the Behaviour of Ballan Wrasse (*Labrus bergylta*) and Lumpfish (*Cyclopterus lumpus*) in Commercial Scottish Salmon Sea-Pens." *Aquaculture* 495: 1–12.

Lee, D., S. Kim, M. Park, and Y. Yang. 2014. "Weight Estimation of the Sea Cucumber (*Stichopus japonicas*) Using Vision-based Volume

Measurement." *Journal of Electrical Engineering & Technology* 9, no. 6: 2154–2161.

Lee, D., and S. N. Yoon. 2021. "Application of Artificial Intelligence-based Technologies in the Healthcare Industry: Opportunities and Challenges." *International Journal of Environmental Research and Public Health* 18, no. 1: 271.

Lee, P. G. 2000. "Process Control and Artificial Intelligence Software for Aquaculture." *Aquacultural Engineering* 23, no. 1-3: 13–36.

Lei, K., C. Zong, T. Yang, et al. 2022. "Detection and Analysis of Sow Targets Based on Image Vision." *Agriculture* 12, no. 1: 73.

Li, D., Q. Wang, X. Li, M. Niu, H. Wang, and C. Liu. 2022. "Recent Advances of Machine Vision Technology in Fish Classification." *ICES Journal of Marine Science* 79, no. 2: 263–284.

Li, W., R. Li, J. Fu, and X. Peng. 2022. "MSENet: A Multi-Scale Enhanced Network Based on Unique Features Guidance for Medical Image Fusion." *Biomedical Signal Processing and Control* 74: 103534.

Li, W., Q. Zhu, H. Zhang, Z. Xu, and Z. Li. 2023. "A Lightweight Network for Portable Fry Counting Devices." *Applied Soft Computing* 136: 110140.

Li, Z., F. Liu, W. Yang, S. Peng, and J. Zhou. 2022. "A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects." *IEEE Transactions on Neural Networks and Learning Systems* 33, no. 12: 6999–7019.

Lin, B., K. Jiang, Z. Xu, et al. 2021. "Feasibility Research on Fish Pose Estimation Based on Rotating Box Object Detection." *Fishes* 6, no. 4: 65.

Lin, T. Y., P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie. 2017. "Feature Pyramid Networks for Object Detection." In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 936–944.

Lines, J. A., R. D. Tillett, L. G. Ross, D. Chan, S. Hockaday, and N. J. B. Mcfarlane. 2001. "An Automatic Image-Based System for Estimating the Mass of Free-Swimming Fish." *Computers and Electronics in Agriculture* 31, no. 2: 151–168.

Liu, S., X. Zheng, L. Han, et al. 2024. "FishMOT: A Simple and Effective Method for Fish Tracking Based on IoU Matching." *Applied Engineering in Agriculture* 40, no. 5: 599–609.

Liu, Z., X. Li, L. Fan, H. Lu, L. Liu, and Y. Liu. 2014. "Measuring Feeding Activity of Fish in RAS Using Computer Vision." *Aquacultural Engineering* 60: 20–27.

López-Patiño, M. A., J. Hernández-Pérez, M. Gesto, M. Librán-Pérez, J. M. Míguez, and J. L. Soengas. 2014. "Short-term Time Course of Liver Metabolic Response to Acute Handling Stress in Rainbow Trout, *Oncorhynchus mykiss*." *Comparative Biochemistry and Physiology Part A: Molecular & Integrative Physiology* 168: 40–49.

Lopez-Tejeida, S., G. M. Soto-Zarazua, M. Toledano-Ayala, L. M. Contreras-Medina, E. A. Rivas-Araiza, and P. S. Flores-Aguilar. 2023. "An Improved Method to Obtain Fish Weight Using Machine Learning and NIR Camera With Haar Cascade Classifier." *Applied Sciences* 13, no. 1: 69.

Lorenzen, K. 2016. "Toward a New Paradigm for Growth Modeling in Fisheries Stock Assessments: Embracing Plasticity and Its Consequences." *Fisheries Research* 180: 4–22.

Mandal, A., and A. R. Ghosh. 2024. "Role of Artificial Intelligence (AI) in Fish Growth and Health Status Monitoring: a Review on Sustainable Aquaculture." *Aquaculture International* 32, no. 3: 2791–2820.

Marrable, D., S. Tippaya, K. Barker, et al. 2023. "Generalised Deep Learning Model for Semi-Automated Length Measurement of Fish in Stereo-BRUVS." *Frontiers in Marine Science* 10: 1171625.

Martinez-de Dios, J. R., C. Serna, and A. Ollero. 2003. "Computer Vision and Robotics Techniques in Fish Farms." *Robotica* 21, no. 3: 233–243.

Martínez-Vázquez, J M., D G. Valcarce, M F. Riesco, V. S. Marco, M. Matsuoka, and V. Robles. 2019. "Artificial Neural Network (ANN) as a Tool to Reduce Human-Animal Interaction Improves Senegalese Sole Production." *Biomolecules* 9, no. 12: 778.

Miao, W., and W. Wang. 2020. "Trends of Aquaculture Production and Trade: Carp, Tilapia, and Shrimp." *Asian Fisheries Science* 33, no. S1: 1–10.

Mikołajczyk, A., and M. Grochowski. 2018. "Data Augmentation for Improving Deep Learning in Image Classification Problem." In *2018 International Interdisciplinary PhD Workshop (IIPhDW)*. IEEE, 117–122.

Mohanty, A., A. Balasundaram, and A. Shaik. 2022. "A Comprehensive Analysis of Deep Learning Frameworks to Mitigate the Impact of Varied Lighting and Weather Conditions." In *2022 Third International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*. IEEE, 1–5.

Momose, H., T. Kaneko, and T. Asai. 2020. "Systems and Circuits for AI Chips and Their Trends." *Japanese Journal of Applied Physics* 59, no. 5: 050502.

Muñoz-Benavent, P., G. Andreu-García, J. M. Valiente-González, V. Atienza-Vanacloig, V. Puig-Pons, and V. Espinosa. 2018. "Automatic Bluefin Tuna Sizing Using a Stereoscopic Vision System." *ICES Journal of Marine Science* 75, no. 1: 390–401.

Muñoz-Benavent, P., J. Martínez-Peiró, G. Andreu-García, et al. 2022. "Impact Evaluation of Deep Learning on Image Segmentation for Automatic Bluefin Tuna Sizing." *Aquacultural Engineering* 99: 102299.

Nehemia, A., and J. Maganira. 2012. "Length-Weight Relationship and Condition Factor of Tilapia Species Grown in Marine and Fresh Water Ponds." *Agriculture and Biology Journal of North America* 3: 117–124.

Nian, R., M. Gao, S. Kong, et al. 2020. "Online Fat Detection and Evaluation in Modelling Digital Physiological Fish." *Aquaculture Research* 51, no. 8: 3175–3190.

Nisbet, R., G. Miner, and K. Yale. 2009. *Handbook of Statistical Analysis and Data Mining Applications*. London: Academic Press.

Odone, F., E. Trucco, and A. Verri. 2001. "A Trainable System for Grading Fish From Images." *Applied Artificial Intelligence* 15, no. 8: 735–745.

O'donncha, F., and J. Grant. 2019. "Precision Aquaculture." *IEEE Internet of Things Magazine* 2, no. 4: 26–30.

OECD. 2023. *OECD-FAO Agricultural Outlook 2023–2032*. Paris: OECD/FAO.

Pacal, I., D. Karaboga, A. Basturk, B. Akay, and U. Nalbantoglu. 2020. "A Comprehensive Review of Deep Learning in Colon Cancer." *Computers in Biology and Medicine* 126: 104003.

Pache, M. C. B., D. A. Sant'Ana, J. V. Araújo Rozales, et al. 2022. "Prediction of Fingerling Biomass With Deep Learning." *Ecological Informatics* 71: 101785.

Page, M. J., J. McKenzie, P. Bossuyt, et al. 2021. "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews." *BMJ* 372: n71.

Palmer, M., A. Álvarez-Ellacuría, V. Moltó, and I. A. Catalán. 2022. "Automatic, Operational, High-resolution Monitoring of Fish Length and Catch Numbers From Landings Using Deep Learning." *Fisheries Research* 246: 106166.

Pang, G. 2022. "The AI Chip Race." *IEEE Intelligent Systems* 37, no. 2: 111–112.

Patel, R., and S. Patel. 2020. "A Comprehensive Study of Applying Convolutional Neural Network for Computer Vision." *International Journal of Advanced Science and Technology* 29, no. 6s: 2161–2174.

Petrellis, N. 2021. "Measurement of Fish Morphological Features Through Image Processing and Deep Learning Techniques." *Applied Sciences* 11, no. 10: 4416.

Piccardi, M. 2004. "Background Subtraction Techniques: A Review." In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583)*, Vol. 4, 3099–3104.

Pinkiewicz, T. H., G. J. Purser, and R. N. Williams. 2011. "A Computer Vision System to Analyse the Swimming Behaviour of Farmed Fish in Commercial Aquaculture Facilities: A Case Study Using Cage-Held Atlantic Salmon." *Aquacultural Engineering* 45, no. 1: 20–27.

Powell, A., J W. Treasurer, C L. Pooley, et al. 2018. "Use of Lumpfish for Sea-Lice Control in Salmon Farming: Challenges and Opportunities." *Reviews in Aquaculture* 10, no. 3: 683–702.

Puig-Pons, V., P. Muñoz-Benavent, V. Espinosa, et al. 2019. "Automatic Bluefin Tuna (*Thunnus thynnus*) Biomass Estimation During Transfers Using Acoustic and Computer Vision Techniques." *Aquacultural Engineering* 85: 22–31.

Qiao, X., J. Bao, H. Zhang, F. Wan, and D. Li. 2019. "Underwater Sea Cucumber Identification Based on Principal Component Analysis and Support Vector Machine." *Measurement* 133: 444–455.

Rai, R., M. K. Tiwari, D. Ivanov, and A. Dolgui. 2021. "Machine Learning in Manufacturing and Industry 4.0 Applications." *International Journal of Production Research* 59, no. 16: 4773–4778.

Ranjan, R., K. Sharrer, S. Tsukuda, and C. Good. 2023a. "Effects of Image Data Quality on a Convolutional Neural Network Trained In-Tank Fish Detection Model for Recirculating Aquaculture Systems." *Computers and Electronics in Agriculture* 205: 107644.

Ranjan, R., K. Sharrer, S. Tsukuda, and C. Good. 2023b. "MortCam: An Artificial Intelligence-Aided Fish Mortality Detection and Alert System for Recirculating Aquaculture." *Aquacultural Engineering* 102: 102341.

Redmon, J., S. Divvala, R. Girshick, and A. Farhadi. 2016. "You Only Look Once: Unified, Real-Time Object Detection." In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 779–788.

Ren, S., K. He, R. Girshick, and J. Sun. 2016. "Faster R-CNN: Towards real-time object detection with region proposal networks." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 39: 1137–1149.

Rey Planellas, S., and C. Garcia de Leaniz. 2024. "Fishes." In *The UFAW Handbook on the Care and Management of Laboratory and Other Research Animals*, edited by H. Golledge, C. Richardson, and R. C. Hubrecht, 907–932. Chichester, UK: John Wiley & Sons.

Rico-Díaz, A. J., J. R. Rabuñal, M. Gestal, O. A. Mures, and J. Puertas. 2020. "An Application of Fish Detection Based on Eye Search With Artificial Vision and Artificial Neural Networks." *Water* 12, no. 11: 3013.

Risholm, P., A. Mohammed, T. Kirkhus, et al. 2022. "Automatic Length Estimation of Free-Swimming Fish Using an Underwater 3D Range-gated Camera." *Aquacultural Engineering* 97: 102227.

Romano, N., and C. Zeng. 2017. "Cannibalism of Decapod Crustaceans and Implications for Their Aquaculture: A Review of Its Prevalence, Influencing Factors, and Mitigating Methods." *Reviews in Fisheries Science & Aquaculture* 25, no. 1: 42–69.

Rumelhart, D E., G E. Hinton, and R J. Williams. 1986. "Learning Representations by Back-Propagating Errors." *Nature* 323, no. 6088: 533–536.

Saberioon, M., and P. Císař. 2018. "Automated Within Tank Fish Mass Estimation Using Infrared Reflection System." *Computers and Electronics in Agriculture* 150: 484–492.

Saberioon, M., A. Gholizadeh, P. Cisar, A. Pautsina, and J. Urban. 2017. "Application of Machine Vision Systems in Aquaculture With Emphasis on Fish: State-of-the-Art and Key Issues." *Reviews in Aquaculture* 9, no. 4: 369–387.

Sahoo, P. K, S. Soltani, and A. K. C. Wong. 1988. "A Survey of Thresholding Techniques." *Computer Vision, Graphics, and Image Processing* 41, no. 2: 233–260.

Salhaoui, M., J. C Molina-Molina, A. Guerrero-González, M. Arioua, and F J. Ortiz. 2020. "Autonomous Underwater Monitoring System for Detecting Life on the Seabed by Means of Computer Vision Cloud Services." *Remote Sensing* 12, no. 12: 1981.

Sebastiani, R., F. Montagnini, and D. Dalli. 2013. "Ethical Consumption and New Business Models in the Food Industry. Evidence From the Eataly Case." *Journal of Business Ethics* 114: 473–488.

Setiawan, A., H. Hadiyanto, and C E. Widodo. 2022. "Shrimp Body Weight Estimation in Aquaculture Ponds Using Morphometric Features Based on Underwater Image Analysis and Machine Learning Approach." *Revue D'intelligence Artificielle* 36, no. 6: 905–912.

Shapiro, L. G. 2020. "Computer Vision: The Last 50 Years." *International Journal of Parallel Emergent and Distributed Systems* 35, no. 2: 112–117.

Sharifi, M., M. Fathy, and M. T. Mahmoudi. 2002. "A Classified and Comparative Study of Edge Detection Algorithms." In *Proceedings. International Conference on Information Technology: Coding and Computing*, 117–120.

Shi, C., R. Zhao, C. Liu, and D. Li. 2022. "Underwater Fish Mass Estimation Using Pattern Matching Based on Binocular System." *Aquacultural Engineering* 99: 102285.

Silva, C., R. Aires, and F. Rodrigues. 2023. "A Compact Underwater Stereo Vision System for Measuring Fish." *Aquaculture and Fisheries* 9, no. 6: 1000–1006.

Smith, M L., L N. Smith, and M. F. Hansen. 2021. "The Quiet Revolution in Machine Vision—A State-of-the-Art Survey Paper, Including Historical Review, Perspectives, and Future Directions." *Computers in Industry* 130: 103472.

Stevenson, R. D., and W. A. Woods Jr.. 2006. "Condition Indices for Conservation: New Uses for Evolving Tools." *Integrative and Comparative Biology* 46, no. 6: 1169–1190.

Stoner, A. W. 2012. "Assessing stress and predicting mortality in economically significant crustaceans." *Reviews in Fisheries Science* 20, no. 3: 111–135.

Sun, X., J. Shi, L. Liu, et al. 2018. "Transferring Deep Knowledge for Object Recognition in Low-Quality Underwater Videos." *Neurocomputing* 275: 897–908.

Szegedy, C., V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. 2016. "Rethinking the Inception Architecture for Computer Vision." In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2818–2826.

Tengtrairat, N., W. L. Woo, P. Parathai, D. Rinchumphu, and C. Chaichana. 2022. "Non-Intrusive Fish Weight Estimation in Turbid Water Using Deep Learning and Regression Models." *Sensors* 22, no. 14: 5161.

Tillett, R., N. Mcfarlane, and J. Lines. 2000. "Estimating Dimensions of Free-Swimming Fish Using 3D Point Distribution Models." *Computer Vision and Image Understanding* 79, no. 1: 123–141.

Tonachella, N., A. Martini, M. Martinoli, D. Pulcini, A. Romano, and F. Capoccioni. 2022. "An Affordable and Easy-to-Use Tool for Automatic Fish Length and Weight Estimation in Mariculture." *Scientific Reports* 12, no. 1: 15642.

Ubina, N. A., S.-C. Cheng, C.-C. Chang, S.-Y. Cai, H.-Y. Lan, and H.-Y. Lu. 2022. "Intelligent Underwater Stereo Camera Design for Fish Metric Estimation Using Reliable Object Matching." *IEEE Access* 10: 74605–74619.

Ubina, N. A., H.-Y. Lan, S.-C. Cheng, et al. 2023. "Digital Twin-Based Intelligent Fish Farming With Artificial Intelligence Internet of Things (AIoT)." *Smart Agricultural Technology* 5: 100285.

UK Public General Acts. 2022. *Animal Welfare (Sentience) Act 2022 ch.22*. https://www.legislation.gov.uk/ukpga/2022/22/enacted.

Van Essen, R., A. Mencarelli, A. Van Helmond, et al. 2021. "Automatic Discard Registration in Cluttered Environments Using Deep Learning and Object Tracking: Class Imbalance, Occlusion, and a Comparison to Human Review." *ICES Journal of Marine Science* 78, no. 10: 3834–3846.

Viazzi, S., S. Van Hoestenberghe, B. M. Goddeeris, and D. Berckmans. 2015. "Automatic Mass Estimation of Jade Perch by Computer Vision." *Aquacultural Engineering* 64: 42–48.

Vo, T. T. E., H. Ko, J.-H. Huh, and Y. Kim. 2021. "Overview of Smart Aquaculture System: Focusing on Applications of Machine Learning and Computer Vision." *Electronics* 10, no. 22: 2882.

Wang, G., A. Muhammad, C. Liu, L. Du, and D. Li. 2021. “Automatic Recognition of Fish Behavior With a Fusion of RGB and Optical Flow Data Based on Deep Learning.” *Animals* 11, no. 10: 2774.

Wang, J.-H., S.-K. Lee, Y.-C. Lai, et al. 2020. “Anomalous Behaviors Detection for Underwater Fish Using AI Techniques.” *IEEE Access* 8: 224372–224382.

Welch, G. F. 2021. “Kalman Filter.” In *Computer Vision: A Reference Guide*, edited by K. Ikeuchi, 721–723. Cham: Springer International Publishing.

Wen, G., S. Li, F. Liu, et al. 2023. “YOLOv5s-CA: A Modified YOLOv5s Network With Coordinate Attention for Underwater Target Detection.” *Sensors* 23, no. 7: 3367.

Wilson, P. I., and J. Fernandez. 2006. “Facial Feature Detection Using Haar Classifiers.” *Journal of Computing Sciences in Colleges* 21, no. 4: 127–133.

Wu, Y., Y. Duan, Y. Wei, D. An, and J. Liu. 2022. “Application of Intelligent and Unmanned Equipment in Aquaculture: A Review.” *Computers and Electronics in Agriculture* 199: 107201.

Xiao, Q., Q. Li, and L. Zhao. 2023. “Lightweight Sea Cucumber Recognition Network Using Improved YOLOv5.” *IEEE Access* 11: 44787–44797.

Xu, W., P. Wang, L. Jiang, K. Xuan, D. Li, and J. Li. 2023. “Intelligent Recognition and Behavior Tracking of Sea Cucumber Infected With Vibrio alginolyticus Based on Machine Vision.” *Aquacultural Engineering* 103: 102368.

Yang, H., Y. Shi, and X. Wang. 2022. “Detection Method of Fry Feeding Status Based on YOLO Lightweight Network by Shallow Underwater Images.” *Electronics* 11, no. 23: 3856.

Yu, G., J. Zhang, A. Chen, and R. Wan. 2023. “Detection and Identification of Fish Skin Health Status Referring to Four Common Diseases Based on Improved YOLOv4 Model.” *Fishes* 8, no. 4: 186.

Yu, X., Y. Wang, J. Liu, J. Wang, D. An, and Y. Wei. 2022. “Non-Contact Weight Estimation System for Fish Based on Instance Segmentation.” *Expert Systems with Applications* 210: 118403.

Zhang, L., W. Li, C. Liu, X. Zhou, and Q. Duan. 2020. “Automatic Fish Counting Method Using Image Density Grading and Local Regression.” *Computers and Electronics in Agriculture* 179: 105844.

Zhang, L., X. Zhou, B. Li, H. Zhang, and Q. Duan. 2022. “Automatic Shrimp Counting Method Using Local Images and Lightweight YOLOv4.” *Biosystems Engineering* 220: 39–54.

Zhang, S., X. Yang, Y. Wang, et al. 2020. “Automatic Fish Population Counting by Machine Vision and a Hybrid Deep Neural Network Model.” *Animals* 10, no. 2: 364.

Zhang, T., Y. Yang, Y. Liu, et al. 2024. “Fully Automatic System for Fish Biomass Estimation Based on Deep Neural Network.” *Ecological Informatics* 79: 102399.

Zhang, T. Y., and C. Y. Suen. 1984. “A Fast Parallel Algorithm for Thinning Digital Patterns.” *Communications of the ACM* 27: 236–239.

Zhang, W., C. Wu, and Z. Bao. 2022. “DPANet: Dual Pooling-aggregated Attention Network for Fish Segmentation.” *IET Computer Vision* 16, no. 1: 67–82.

Zhang, Y., D. Zhou, S. Chen, S. Gao, and Y. Ma. 2016. “Single-Image Crowd Counting via Multi-Column Convolutional Neural Network.” In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 589–597.

Zhang, Y. Z., F. Zhang, J. Cheng, and H. Zhao. 2021. “Classification and Recognition of Fish Farming by Extraction New Features to Control the Economic Aquatic Product.” *Complexity* 2021: 5530453.

Zhou, C., K. Lin, D. Xu, et al. 2018. “Near Infrared Computer Vision and Neuro-Fuzzy Model-Based Feeding Decision System for Fish in Aquaculture.” *Computers and Electronics in Agriculture* 146: 114–124.

Zhou, C., D. Xu, L. Chen, et al. 2019. “Evaluation of Fish Feeding Intensity in Aquaculture Using a Convolutional Neural Network and Machine Vision.” *Aquaculture* 507: 457–465.

Zhou, K., X. Meng, and B. Cheng. 2020. “Review of Stereo Matching Algorithms Based on Deep Learning.” *Computational Intelligence and Neuroscience* 2020: 1–12.

Zhou, L., L. Zhang, and N. Konz. 2023. “Computer Vision Techniques in Manufacturing.” *IEEE Transactions on Systems Man Cybernetics-Systems* 53, no. 1: 105–117.

Zhou, M., P. Shen, H. Zhu, and Y. Shen. 2023. “In-water Fish Body-length Measurement System Based on Stereo Vision.” *Sensors* 23, no. 14: 6325.

Zhu, J., W. He, W. Weng, et al. 2022. “An Embedding Skeleton for Fish Detection and Marine Organisms Recognition.” *Symmetry* 14, no. 6: 1082.

Zou, J., Y. Han, and S.-S. So. 2008. “Overview of Artificial Neural networks.” In *Artificial Neural Networks: Methods and Applications*, edited by D. J. Livingstone, 15–23. Clifton, N.J., USA: Humana Press.