Journal of Computers Vol. 31 No. 1, 2020, pp. 294-319
doi:10.3966/199115992020023101028

Deep Learning in Aquaculture: A Review

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Received 2 November 2019; Revised 2 December 2019; Accepted 11 January2020

Abstract. Aquaculture is a complex, multicomponent, interactive process that is dependent on water resource, animal, human as well as capital investment. The measured data affected by complicated environmental factors are usually nonlinear and various, which make it difficult to accurately control system. Traditional machine learning methods have not satisfied the actual requirements because these models can't extract intrinsic features of data. As an important branch of machine learning, deep learning has been emphasized in both academia and industry due to the specialty of automatic feature extraction from raw data. Accordingly, application of deep learning in aquaculture is expected to produce promising results. Quite a number of researches have highlighted its potential for detection, classification, counting and prediction tasks in aquaculture. Here, we review application of deep learning in aquaculture, and categorize research by aquatic products (i.e. fish, shrimp, scallop, coral, jellyfish, aquatic macroinvertebrates, phytoplankton and water quality), presenting examples of current research in each object. The studies involve fish classification, fish counting, fish behavior monitoring, fish fillets defect detection, shrimp disease research, shrimp freshness detection, pearl classification, scallops counting, coral species classification, activity monitoring of cold water coral polyps, jellyfish detection, aquatic macroinvertebrates classification, phytoplankton classification, trend prediction of red tide biomass, dissolved oxygen content prediction, chlorophyll-a content prediction, temperature prediction, marine floating raft aquaculture monitoring, obstacle avoidance in underwater environments and virtual fish grasp. We found that deep learning technique achieved higher accuracy and efficiency than other methods in most studies. In addition, advantages and limitations of deep learning in aquaculture were discussed, with recommendation on future research directions and challenges. We hope that this review will provide valuable insights to advance aquaculture in future research.

Keywords: aquaculture, deep learning, neural network

1 Introduction

China is the largest aquaculture country in the world, whose aquaculture production accounts for 60 percent of global total. Aquaculture is a complex, multicomponent, interactive process that is dependent on water resource, animal, human as well as capital investment. There are a wide variety of aquatic organisms in aquaculture, including fish, shrimp, crab, scallop, coral, jellyfish, aquatic macroinvertebrate, phytoplankton. And good quality of water is the essential existence condition for aquaculture organisms,

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which directly affects the growth of aquaculture organisms and diet safety of aquatic products. The measured data affected by complicated environmental factors are usually nonlinear and various, which make it difficult to accurately control system. Traditionally, cameras, underwater robots and water quality sensors are mainly used to monitor the entire production process of aquaculture. Some traditional machine learning algorithms (i.e. Support Vector Ma-chines (SVMs), K-means, random forests (RF), backpropagation neural network (BPNN) have been applied in aquaculture [1-3]. However, the image data captured by underwater cameras or robots are always low quality due to luminosity change, turbidity, complex background and fast-moving aquatic animals. Traditional ma-chine learning methods have not satisfied the actual requirements because these models can't extract intrinsic features of data. And the manual-designed features are susceptible to the human error. However, deep learning, as an important branch of machine learning, can learn hierarchical representations of raw data automatically by simulating the human neural network. Therefore, applying deep learning in aquaculture is of great significance to solve actual problems.

As an important branch of machine learning, the strongest characteristic of deep-learning methods is representation-learning methods with multiple levels of representation, which can obtain the simple features automatically from the raw input and transform the lower level representation into a higher, slightly more abstract level representation [4]. One common definition of deep learning is "A class of machine learning techniques that exploit many layers of non-linear information processing for supervised or unsupervised feature extraction and transformation, and for pattern analysis and classification" [5]. Most deep neural networks can be classified into three major categories [5]:

Deep networks for unsupervised learning: refer to no use of task specific supervision in-formation in the learning process. There are common models for unsupervised learning including Restricted Boltzmann machine (RBM), Deep Belief Network (DBN), Deep Boltzmann Machine (DBM), Recurrent Neural Network (RNN) and Sum–product network (SPN), Autoencoders (AE).

Deep networks for supervised learning: refer to use only with labeled data in the learning process and all outputs must be tagged. There are common models for supervised learning including Deep Stacking Network (DSN), RNN and Convolutional Neural Network (CNN).

Hybrid or semi-supervised networks: make use of both generative and discriminative model components. Normally, unsupervised data are used to pretrain the network weights to speed up the learning process prior to the supervision stage [6].

The most commonly used deep learning architectures include CNN, RNN, AE. CNN is a variant of the Multi-layer perceptron (MLP) with convolutional layers, pooling layers and fully connected layers [7]. CNN is designed to process two-dimensional data. CNN is a feedforward neural network that ex-tracts its topology from a two-dimensional data using a back-propagation algorithm to optimize the network structure and solve unknown parameters in the networks [7-9]. CNN is a typical supervised learning model with strong adaptability. It is good at mining data local features and extracting global training features. And CNN has achieved good results in various fields of pattern recognition [10-12]. Unlike the feedforward neural networks, RNN can use its internal memory to process input sequences of arbitrary timing, which makes it easier to handle sequential information such as text, speech, and language. It is hard for RNN to store information for very long time and the gradient may vanish [13]. Long short-term memory networks (LSTM) and gated recurrent unit (GRU) were proposed to address such issues, with gating mechanisms to manipulate information through recurrent cells [14-15]. At pre-sent, RNN has been successfully applied in speech recognition, language modeling, handwriting recognition, translation and picture description. AE is a neural network that reproduces the input signal as much as possible. In other words, AE gets useful high-level features that can represent the input data, which is similar to Principal Component Analysis (PCA) method. According to different demands, many variants of AE are produced, such as stacked autoencoder (SAE), denoise autoencoder (DAE), contractive autoencoder (CAE). In this review, we only provide a brief introduction to the following three typical models that have already been used in the agriculture filed and can be embedded into the general framework to fulfill the specific tasks. More detailed information regarding deep leaning can be found in [4] and [5]. Deep learning has been widely applied in medicine [16], agriculture [17], re-mote sensing [18], industry [19], business [20] and transportation fields [21]. Fig. 1. shows a general CNN architecture for fish classification, which consists of convolution layers, pooling layers and fully connected layers.

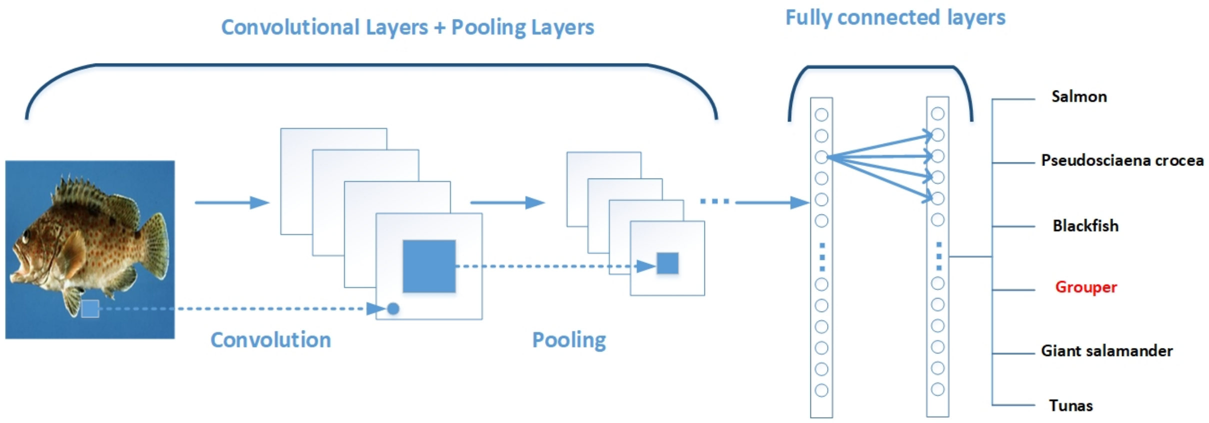

Fig. 1. A general CNN architecture for fish classification

Although recently published reviews [17] discussed deep learning applications in agriculture research, it didn't involve the application research in aquaculture. In this article, we provide a more comprehensive review of deep learning for aquaculture and research examples were categorized by aquatic product (i.e. fish, shrimp, scallop, coral, jellyfish, aquatic macroinvertebrates, phytoplankton and water quality). This article aims to provide valuable insight for application of deep learning to advance aqua-culture in future research. To the best of our knowledge, we are one of the first groups to review deep learning applications in aquaculture.

Table 1. Abbreviations in alphabetical order

Abbreviation	Full word
ACE	Automatic color enhancement
AE	Autoencoder
ANN	Artificial neural networks
AUV	Autonomous underwater vehicle
AP	Average precision
BP	Back propagation
BPNN	Back propagation neural network
CAE	Contractive autoencoder
CNN	Convolutional neural network
CRBM	Conditional restricted Boltzmann machines
DAE	Denoise autoencoder
DBM	Deep Boltzmann machine
DBN	Deep belief network
DCSCN	Deep collaborative sparse coding network
DeConv	Deconvolutional neural networks
DSN	Deep stacking network
ELM	Extreme learning machine
FCN	Fully convolutional network
GAN	Generative adversarial network
GRU	Gated recurrent unit
GT	Groundtruth
HSI	Hyperspectral imaging
LSSVM	Least squares support vector machine
LSTM	Long-short term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MLP	Multi-layer perceptron
MLPR	Multilayer perceptron regressor
MNMS	Modified non-maximum suppression
MS-CNN	Multi-stream convolutional neural network
NIN	Network in network
NIR	Near-infrared

Table 1. Abbreviations in alphabetical order (continue)

Abbreviation	Full word
PCA	Principal component analysis
PCA-BP	Principal component analysis-Back propagation
PCA-ELM	Principal component analysis-Extreme learning machine
PCA-LSSVM	Principal component analysis-Least squares support vector machine
PCA-LSTM	Principal component analysis-Long- short term memory
PCANet	Principal Component Analysis Network
PCA-PSO-BP	Principal component analysis-Particle swarm optimization-Back propagation
PSO	Particle swarm optimization
RBM	Restricted Boltzmann machine
RF	Random forest
RFID	Radio Frequency Identification
RMSE	Root mean square error
RNN	Recurrent neural network
SAE	Stacked auto-encoder
SAENN	Sparse autoencoder based neural network
SAR	Synthetic aperture radar
SOMP	Simultaneous orthogonal matching pursuit
SPN	Sum–product network
SPP	Spatial pyramid pooling
SSAE	Stacked sparse auto-encoder
SVM	Support vector machine
SVR	Support vector regression
TD-LSTM	Temporal dependence-based LSTM
TVB-N	Total volatile basic nitrogen
UAV	Unmanned aerial vehicle

2 Applications and Results in Aquaculture

With the rapid development of aquaculture and its intensive extensively expansion, modern aquaculture will face more opportunities and challenges. Modern aquaculture demands more automated and precise. Some studies have applied deep learning technology to solve various problems and challenges in aquaculture (i.e. fish classification, fish counting, fish behavior monitoring, fish fillets defect detection, shrimp disease research, shrimp freshness detection, pearl classification, scallops counting, coral species classification, activity monitoring of cold water coral polyps, jellyfish detection, aquatic macroinvertebrates classification, phytoplankton classification, trend prediction of red tide biomass, dissolved oxygen content prediction, chlorophyll-a content prediction, temperature prediction, marine floating raft aquaculture monitoring, obstacle avoidance in underwater environments and virtual fish grasp). In this section, deep learning applications in aquaculture are reviewed. Fig. 2 shows the relevant researches in aquaculture.

2.1 Fish

According to commercial requirement, fish classification, fish counting, fish behavior monitoring and fish products assortment are important processes during fish farming and processing. Usually, these demands include more precise classification, prediction and estimation results and faster processing speed. This creates incentives to find more accurate methods for fish classification, fish counting, fish behavior monitoring and fish products assortment tasks.

2.1.1 Fish Classification

Underwater object recognition is in great demand among the important tasks of ocean observation and fish farming monitoring. However, fish recognition is a challenging research issue because there are many challenges in real underwater environment, such as changing light radiation, water turbidity,

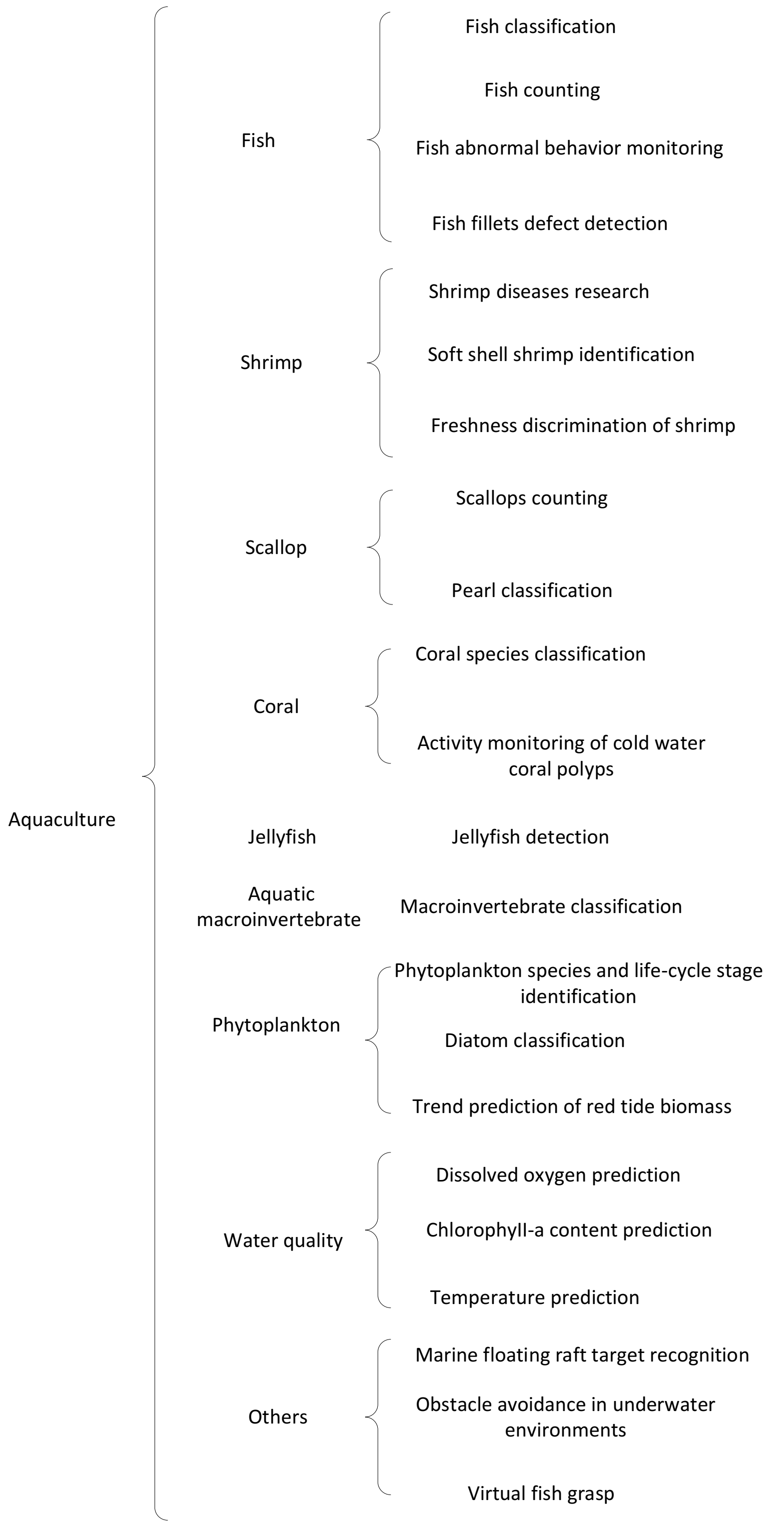

Fig. 2. The relevant researches in aquaculture

background confusion, bio-fouling growth on the camera housing and moving aquatics. The fish recognition task is actually a fine-grained classification problem due to variations in lighting, pose, background, and water turbidity. Therefore, conventional shallow machine learning algorithms and image processing techniques are not applicable for this task. Qin et al. [22] proposed a novel framework based on a simple cascaded deep network for live fish recognition. Inspired by the method in [23], they extracted the foreground fish masks from the videos via sparse and low-rank matrix decomposition. In the network, PCA was used in first two convolutional layers, followed by binary hashing in the nonlinear layer and block-wise histograms of the binary codes in the feature pooling layer. Then spatialpyramid pooling (SPP) is used to extract information invariant to large poses. Finally, the final output was fed to a linear SVM classifier. The proposed networks achieved 98.64% for 23 fish species on the Fish Recognition Ground-Truth dataset, which was comparable with their carefully designed and tuned deep CNN architecture (98.57%). The results indicated the incorporation of different deep networks is a promising future trend. Siddiqui et al. [24] proposed a pre-trained convolutional neural network with a linear SVM Classifier for fish species classification from typical underwater video imagery. They presented a special cross-layer pooling approach that combined features from two different layers of a pre-trained CNN to enhance discriminative ability. The fused features were passed to a linear SVM Classifier for final classification. However, the cross-layer pooling pipeline increased the computation so much that it precluded the possibility of real time processing. With the other species class included, the classification accuracy reached 89.0%. The classification accuracy for only 16 fish species was 94.3%, which was competitive with other recently reported results on fish species identification tasks [25-33]. The study suggested the usage of the pre-trained network for classification tasks without an external classifier would be a promising future research direction. Kutlu et al. [34] applied DBN to classify 3 species of Triglidae family with a high accuracy rate of 97.61%. The morphometric features were firstly extracted using 13 landmarks. Then DBN model was used for the classification task. Though achieving high classification accuracy, the proposed method increased the complexity of algorithm due to the morphometric features' extraction in advance. In order to improve the performance of these tasks, some studies detect fish in advance [35-37]. Fig. 3. shows the fish detection before fish classification. The image data are obtained from Kaggle dataset.

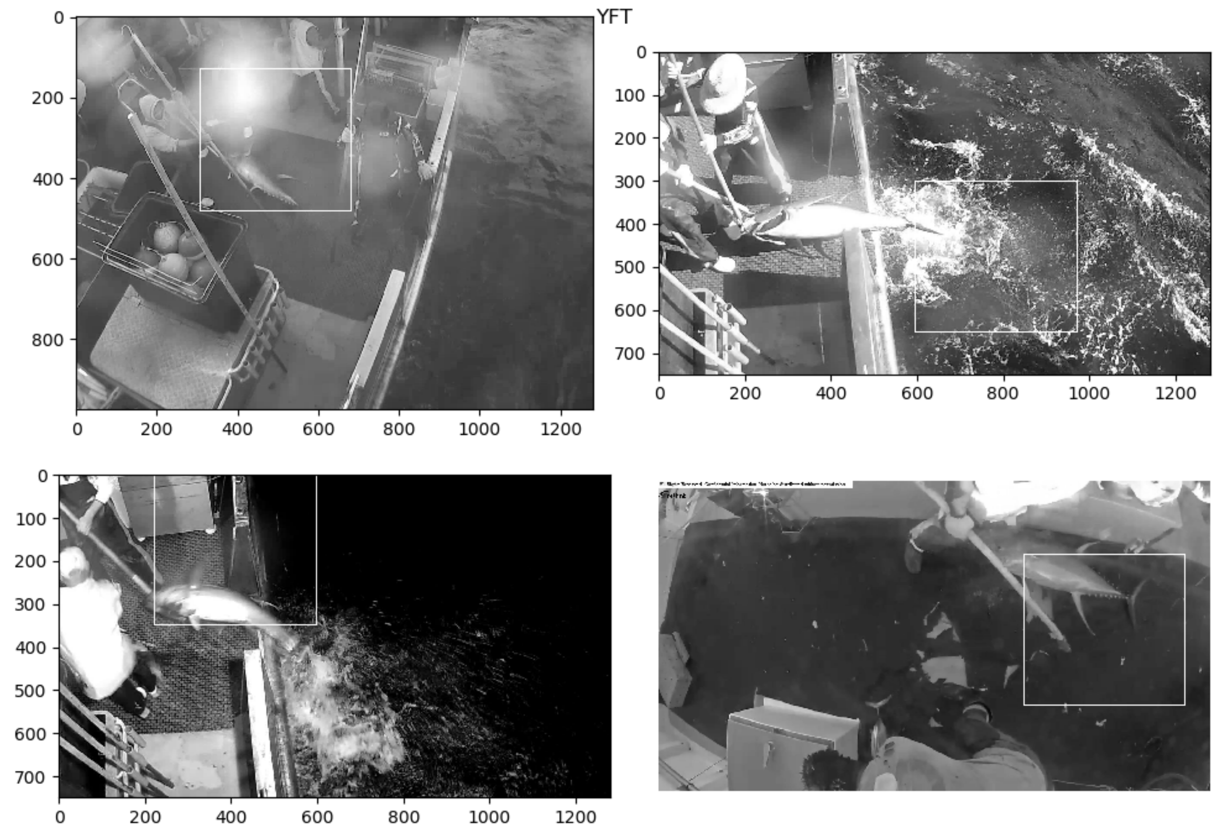

Fig. 3. Fish detection

The literatures on fish classification referenced above all utilized the image data to perform the tasks of fish classification and recognition. However, Ibrahim et al. [38] classified different species of groupers by their vocalizations. They firstly used wavelet denoising to reduce ambient ocean noise. Then LSTMs and CNNs were used for classification. The proposed approach achieved a classification accuracy of around 90%, which performed better than [39].

The underwater environment is so complicated that the images' quality is poor. To overcome the low-resolution problem of underwater images, Sun et al. [40] applied a single-image super resolution method to produce high resolution images from lower ones. Motivated by a fast-direct super-resolution method proposed by Yang et al. (2013) [40], they split the feature space into several subspaces to get simple mapping functions from training image patches for each subspace. Then a self-mechanism of high-resolution image generation was proposed. Then two deep learning methods including Principal Component Analysis Network (PCANet) [41] and Network In Network (NIN) [42] were used to extract features from images. The linear SVM was finally used for fish recognition. However, the best classification accuracy of 77.27% wasn't enough for practical application.

The processing of underwater images is one of the most challenging problems in aquaculture due to light transmission in water. Although traditional image restoration techniques correctly remove the haze in a degraded image, they cannot be used in a real time system due to the requires of multiple im-ages from same location and several parameters measurement. Therefore, Perez et al. [43] combined deep learning technology with image restoration techniques to dehaze single images. This system trained a convolutional neural network with a dataset of pairs of raw and restored images, which can correctly dehaze images in real time with a single image as input. The generalization capability of the proposed approach was better than other image enhancement methods, which was able to dehaze with images from a location and be used in a different location. The performance of the approach was slightly worse in a different location, but still outperform other methods such as Automatic Color Enhancement (ACE), Ground-truth (GT), histogram equalization.

The underwater images have many problems such as noise pollution, occlusion, low-contrast, blur-ring and so on. Therefore, many studies used manual annotation to improve the performance of the fish classification tasks. However, the manual annotation way is time-consuming, laborious, and prone to errors. An unsupervised underwater fish detection approach was proposed by Zhang et al. [44]. They used motion flow segmentations and Selective Search to generate fused region proposals. Then the CNN model was used to classify all proposed samples to compute confidence. In addition, Modified Non-Maximum Suppression (MNMS) was applied to find unique regions per object to reduce false classifications in detection. The Average Precision (AP) of fish detection was improved by about 10% compared to non-fusion approach and about another 10% by using MNMS. The results showed the proposed method helped to detect the fish more accurately on the poor-quality underwater images.

In addition, some special types of fish are also applied in the fields of medicine, biology, genomics, food technology and biomedical research. Zebrafish (Danio rerio) is an important vertebrate model organism for biomedical research due to their transparency at birth, their rapid development and short generation times. Ishaq et al. [45] used a pre-trained CNN model for accurate high-throughput classification of whole-body zebrafish deformations due to drug-induced neuronal damage in response to camptothecin. The classification accuracy of 92.8% was achieved. They found that the morphology of the head region of the fish was more important as a discriminating feature than the visually apparent bend of the tail region. The study indicated deep learning has the potential to discriminate between wild-type morphology and phenotypes in response to drug treatment.

2.1.2 Fish Counting

Fishing controls help to provide sustainable economic, environmental and social conditions. In the past, some people were arranged to monitor the number, size and species of fish caught by reviewing the video footage, which was a tedious and costly task. To reduce the viewers' workload and automate this procedure, French et al. [46] utilized CNN to monitor discarded fish catch on fishing trawlers for the first time. The dataset consisted of 52 videos from 12 different conveyor belts. The N4-Fields image transformation algorithm was used in this study for foreground segmentation. Firstly, the training images were extracted overlapping patches. Then PCA was used to reduce the dimensionality. A CNN-based regressor was trained to map input patches. Then the input patches were mapped to the output patches. The output patches were added to the output image. The relative count error for individual fish ranged from 2% to 16%. The counting accuracies of 3 of six belts only met the project requirement. There is still room for improvement in performance of the proposed method.

2.1.3 Fish Behavior Monitoring

Abnormal behavior monitoring of fish school plays a crucial role in water quality monitoring and can provide early warnings of fish disease. Previous related works are mainly based on the foreground segmentation and multi-target tracking [47-49]. However, it is hard to be implemented in practical intensive aquaculture. An alternative to above tracking-based methods was proposed by Zhao et al. [50]. They presented modified motion influence map and RNN for the local unusual behaviors monitoring of fish school in intensive aquaculture. The particle advection scheme was firstly used to extract motion characteristics of the whole fish school, which made tracking and foreground segmentation avoided. Then, modified motion influence map was used to detect and localize the local unusual behaviors of fish school. Finally, RNN was applied for the recognition of the local unusual behaviors. This study involved three typically local unusual behaviors. The accuracies of the presented method were 98.91%, 91.67% and 89.89% for detection, localization and recognition, respectively. The performance of the proposed method was better than many other state-of-the-art methods [51-52]. The experiment in the paper was done under the assumption that water is clear. However, the real aquaculture water is muddy with different impurities. These impurities have one downside to the capture of clear fish motion images.

2.1.4 Fish Fillets Defect Detection

The detection, recognition and localization of food defects have proven to be extremely challenging in food manufacture. For fish fillets, blood spots are detrimental to their quality and reduce their market value. The manual classification method hasn't met the needs of modern industry. The modern industry requires a robust, rapid, effective, automated, non-invasive and low-cost method for the classification of normal and defective fish fillets. Misimi et al. [53] used pre-trained CNN and SVM models for accurate segmentation and localization of blood spots and the classification of defective cod fish fillets. A novel data augmentation method was proposed in this study that desensitized the CNN for shape and focused only on color features for the classification between normal and defective fish fillets. The 3D information was used to localize the blood spots and calculate the relevant gripper vectors, as an input to robotic processing. Based on Graphical Processing Unit (GPU), the classification accuracy of CNN model achieved 100%, which was slightly better than SVM model. And the CNN model didn't need extract features manually, which was more automated than SVM model. The study demonstrated that synergies of computer vision, deep learning and robotics will be a future research direction in food manufacture.

2.2 Shrimp

Shrimp production is one of the important global seafood industries. However, viral and bacterial diseases are major threats on shrimp production and sustainability. Histology is one of the main tools for disease diagnosis [54]. Previous studies used traditional machine learning methods for disease diagnosis based on histological images [55-56]. The performance of machine learning methods was heavily dependent on the choice of features. Deep learning technology exactly tackles the problem of selecting the features manually. However, the deep learning technology requires a large number of training samples. With the intention of identifying unseen objects on histological images solely based on the information such as text in scientific literature, Mendieta and Romero [54] evaluated a cross-modal transfer approach from text description to images of organs and diseases of shrimps. They selected the best semantic word representation from scientific literature. Then, they extracted the most relevant features from histological images (healthy shrimps, sick shrimps with white spot syndrome virus and sick shrimps with vibriosis). They constructed a cross-modal learning model to artificially generate a new image by mapping between word-representations and image representations. The method provided an alternative solution to the problem of limited and imbalanced data. However, the work was just a case study which didn't show the specific performance.

Soft shell shrimp are common phenomenon in shrimp farming, which have great similarity with sound shrimp in appearance. The soft shell shrimp occur due to lacking of calcium salt compound in the shrimp shell, and the soft shell is often related to some diseases. Earlier works used elaborate features (texture, shape and color) to classify the soft shell shrimp from sound shrimp [57]. However, the designed features are dependent on human ingenuity and prior knowledge and the classification accuracy is also limited. Aiming at the problems, Liu et al. [58] applied Sparse Autoencoder based Neural Networks (SAENN) to automatically learn the features for the visual localization and classification of soft shell shrimp. In order to train the networks efficiently, the proposed method divided one single image into many sub-images. They extracted 50 sub-images in each shrimp image. Then, they labelled these sub-images (sound shrimp with "1" and soft shell shrimp with "2"). Then, they computed the numbers of labels of sound shrimp ("1") and labels of soft shell shrimp ("2") based on majority rule. The label with huge numbers was chosen as the final label of the original image. The proposed method achieved a mean accuracy more than 98.05%. The result indicated the deep learning algorithm was feasible to be used in automatic shrimp classification systems.

Shrimp have a high nutritional value. However, the shrimp is hard to preserve. Deteriorated shrimp have many spoilage microorganisms [59], which are harmful to human well-known. Increasing emphasis on shrimp quality and safety is a major driving force to establish rapid and nondestructive freshness detection systems. To discriminate the freshness of shrimp during cold storage, Yu et al. [60] proposed SAEs and logistic regression to detect freshness grade of shrimp based on hyperspectral imaging (HSI) technology. In this study, all shrimps were classified into two freshness grades: fresh and stale according to their total volatile basic nitrogen (TVB-N) contents (the fresh samples with a TVB-N value below 30.00 mg N/100g and the stale samples with a TVB-N value above 30.00 mg N/100g). Hyperspectral images have been proved to be feasible for predicting TVB-N content in shrimp. The SAEs was used to extract the spectral features from hyperspectral images. Then, the logistic regression model was used to classify the freshness grade of shrimp. The total classification accuracy of the proposed method reached 96.55% and 93.97% in calibration and prediction sets, respectively. The results demonstrated that deep learning algorithm was feasible and effective to detect freshness of shrimp.

2.3 Scallop

For scallops, counting also needs sequential images. Common fixed cameras couldn't capture the scallop images because the scallops belong to benthic creatures. A new counting method of scallops based on deep learning technology was studied by Rasmussen et al. [61]. They presented a convolutional neural network for vision-based counting of wild scallops using sequential images collected by an autonomous underwater vehicle (AUV). The YOLOv2 architecture was used in this study due to the high object detection accuracy and real-time speed. The images needed be processed duo to the low brightness and color contrast. Then, images were annotated manually, and they trained a separate denoising auto-encoder network to upgrade automatically these annotations, thereby enabling efficient augmentation of the training data. Then, they used a neural network to automatically upgrade the original rough positions to bounding boxes. Finally, they trained the network to output a "heatmap", where high-value pixels belong to the scallop and low-value pixels to the background. The system achieved high accuracy of 84.7% and real-time speeds. Note that this study focused on simply identifying healthy scallops. There still was some limitation in this study such as double-counting the same scallop. Adding compromised scallops, removing other relevant creatures and automatic contrast enhancement on the raw images could be taken into account in this study.

Pearls are the products of some shellfishes and have a high value for commerce and appreciation. Most pearl-producing companies rely mainly on manual classification, which is inefficient. And there isn't a clear and unified classification standard. Some studies applied the machine learning method for fault diagnosis [62]. However, for pearl classification, it is quite difficult to design the effective hand-crafted features. Xuan et al. [63] proposed a novel multi-stream convolutional neural network (MS-CNN) method to classify pearls into two classed and seven classes using pearl images of five different viewing angles. They designed a pearl classification machine which consisted of four parts: feeding mechanism, delivering mechanism, vision-based detection device, and classification mechanism. The detection device got images of five views for each pearl, i.e., top, left, right, main, and rear. These multi-view images were taken as the inputs to the respective streams. Pearls were classified into two classes by rough rules or seven classes by fine rules. The proposed method achieved 92.14% and 91.24% test accuracies for two-class and seven-class classification tasks, respectively, which were much better than SVM and BPNN based on hand-crafted features. The study may help the pearl industry save a large number of labors and formulate a unified classification standard.

2.4 Coral

The repair of deep-sea coral reefs is vital for the oceans ecosystem. In order to locate a coral reef and a chunk of coral on the seabed and prompt the robot to pick it up, Robertson [64] presented CNNs for coral species classification. These corals were classified into 5 coral classes and 4 non-coral classes. The best overall accuracy was about 60%. The performance of the proposed method still needs improvement.

Coral polyps are an important part of coral reefs. Osterloff et al. [65] presented convolutional neural networks to automatically monitor the activity of cold water coral polyps. Images were firstly preprocessed to reduce color fluctuations and camera shifting. Images annotations were placed manually. A gold standard was generated by three observers on a region of interest in 13 images. The gold standard helped enhance the reliability of the manual annotations. A CNN on the gold standard was trained for the polyp activity automatic classification. The classification accuracy reached 98% and 96% for the training set and the test set, respectively. However, the method was sensitive to the quality of the manual annotations. Observers may have varying numbers of annotations because they only identified the activity-level polyps.

2.5 Jellyfish

Jellyfish blooms have caused environmental and economic damage to fisheries. Kim et al. [66] built a jellyfish removal robot system. The system removed jellyfish by manual operation or semi-automatic operation using jellyfish detection algorithms. And the operation area was limited. To increase the efficiency of the system [66], Zhang et al. [67] proposed a unmanned aerial vehicle (UAV)-type surveillance system. The proposed system could observe jellyfish on the surface of the sea while flying and could recognize a herd of jelly-fish using deep learning algorithm. Image processing techniques were used for denoising and jellyfish segmentation. Then, a convolutional neural network was used to recognize jellyfish. The recognition accuracy of the proposed system reached 80%. However, it didn't cover all types of harmful jellyfish. The study only involved the 'Aurelia aurita'. And the recognition performance of this study still needs improvement. Furthermore, Kim and Myung [68] proposed a novel autoencoder-combined generative adversarial network to generate synthetic images of the jellyfish. The autoencoder was added to make a boundary to the generative adversarial network (GAN) output image in order to increase the stability of the GAN. Then they utilized a fully convolutional network (FCN) and regression network to estimate the size of the jellyfish swarm. The FCN was trained with the synthetic ocean scene and the results showed an accuracy of 83.8% on real test dataset, which outperformed the result with 80.5% accuracy in Zhang et al. [67].

2.6 Aquatic Macroinvertebrates

Aquatic macroinvertebrate biomonitoring is an efficient way of assessment of ecological status of the aquatic ecosystem. Riabchenko et al. [69] propose CNNs for macroinvertebrate classification. The proposed method achieved 85.64% classification accuracy for 29 macroinvertebrate classes, which was close to human taxa identification accuracy (typically 90-95% on 30-40 classes of macroinvertebrates). This work compared CNN trained from scratch with fine-tuned CNN. The result found that the latter performed better than the former. It showed the transfer learning could get good performances in this study while saving training time. Furthermore, Raitoharju et al. [70] presented a new benchmark data-base of benthic macroinvertebrates, which contained 64 types of freshwater macroinvertebrates, ranging in number of images per category from 7 to 577. The database was made public for the purpose of automatic fine-grained classification.

2.7 Phytoplankton

Phytoplankton monitoring plays a key role in water quality assessment of aquaculture. The traditional phytoplankton analysis method is strongly limited by microscopic techniques and taxonomic expertise. To overcome these hurdles, Dunker et al. [71] utilized CNN model for phytoplankton species and life-cycle stage identification. The life-cycle stage was divided into stationary phase, early exponential phase and exponential phase. The phytoplankton species identification and their respective life cycle stage could be predicted with a high accuracy of 97% when using a classifier trained on merged bright-field and Chl *a* fluorescence images.

Diatoms are often used for water quality determination in aquaculture because of its rich nutrition and long life-cycle. Pedraza et al. [72] applied CNN model to classify diatom. The dataset used in this study involved 80 diatom types with different illumination conditions. An overall accuracy of 99% was obtained in the experiment. The misclassification was caused by different views for the same diatom type. In addition, as far as the author of this paper was concerned, the paper was the first time to apply CNN model for diatom classification.

In recent years, harmful algal blooms have increased in China, which have made a great negative impact on marine ecosystem, aquaculture and human health. A novel method was proposed by Zhou. [73] to predict the trend of red tide biomass in the coastal waters of Zhejiang Province. It combined Conditional Restricted Boltzmann Machines (CRBM) with DBN model. The Particle Swarm Optimization (PSO) algorithm was used to optimize the network depth and training parameters of CRBM. The prediction accuracy of the proposed method was 72.62%, which was better than DBN, DAE, BP models. The data in this study were only obtained by the ships. Other monitoring ways should also be considered in this study such as ocean buoy monitoring, the shore station monitoring and satellite remote sensing. The continuity of monitoring data could be influenced because sampling interval was half a month in this study.

2.8 Water Quality Prediction

2.8.1 Dissolved Oxygen

Dissolved oxygen content in aquaculture is an important indicator of the status of aquatic animals and water quality, which is susceptible to temperature, wind speed, wind direction, rainfall, aquatic metabolism and human activities. The research on the prediction method of dissolved oxygen content in aquaculture is helpful to prevent water quality deterioration and disease outbreak, and to optimize aquaculture management. Previous studies mainly utilized traditional machine learning methods [74-77]. These methods lack robustness in processing big data, which make the models lack scalability capability and make them unable to fully reflect the essential characteristics of the data. A novel prediction model of dissolved oxygen in aquaculture was proposed by Chen et al. [78] based on PCA and LSTM. PCA was used to extract the key impact factors of dissolved oxygen in aquaculture, which eliminated the correlation among the original variables and reduced the dimension of input vector. Then the selected key impact factors were used as inputs of LSTM network. The mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) of the Principal component analysis-Long short term memory (PCA-LSTM) were 0.274, 0.089 and 0.147, respectively. The performance of the proposed method was better than other networks such as Principal component analysis-Least squares support vector machine (PCA-LSSVM)、Principal component analysis-Particle swarm optimization-Back propagation (PCA-PSO-BP)、Principal component analysis-Back propagation (PCA-BP)、Principal component analysis-Extreme learning machine (PCA-ELM) and LSTM. The proposed method with good predictive performance and generalization ability is able to meet the actual needs of accurate predictions of dissolved oxygen in aquaculture. Similar to Chen et al. [78], Li et al. [79] combined SAE and LSTM network to improve the prediction accuracy of dis-solved oxygen in aquaculture. SAE was used to extract features to enhance the prediction accuracy of LSTM. The MSE of SAE-LSTM was 0.0056, 0.0077 and 0.0242 for 3h, 6h, 12h prediction, respectively. The result showed that SAE-LSTM outperformed LSTM, BPNN and SAE-BPNN.

2.8.2 Chlorophyll-a Content Prediction

The chlorophyll-a content of aquarium water can directly reflect the quality of water, which affects the growth of aquatic animals and plants. Many previous studies utilized machine learning methods to predict the concentration of chlorophyll-a, such as the artificial neural network (ANN) [80-82], SVM [83] and RF [84]. These models are difficult to get the accurate prediction of chlorophyll-a con-tent due to the complexity and non-linearity among the relevant factors. Cho et al. [85] presented LSTM to predict the concentration of chlorophyll-a. The proposed method used daily measured water quality information as input and the content of chlorophyll-a as output. The result showed that LSTM network outperformed the previous approaches, in predicting chlorophyll-a in 4-days prediction as well as 1-day prediction. The slightest test error was 0.04868 for the 1-day prediction task and 0.08015 4-days prediction task. In addition, batch normalization was proved to be a suitable way to help the learning process as regularization method. But the need to pay attention to is that obtained data in this study need to be random shuffling due to the temporal bias among the data set. In addition, as a proxy for algal activity, chlorophyll-a can be used for algal blooms prediction. Sangmok and Lee [86] presented three deep learning models (MLP, RNN, and LSTM) to predict chlorophyll-a content for the purpose of harmful algal bloom prediction. The result showed that the performance of the LSTM model was superior to the MLP and RNN models, with RMSE average of 16.09. There were still some limitations: some missing data values and unstable predicted results. In addition, there still exist some room for higher accuracy.

2.8.3 Temperature Prediction

Temperature is one of the important factors influencing aquatic product growth. Liu et al. [87] analyzed the impact of temporal closeness, period and trend for marine temperature at multiple depths (0m, 50m, 100m, 200m and 500m) and proposed the temporal dependence-based LSTM (TD-LSTM) network for ocean-temperature prediction, which utilized the temporal dependence parameter matrix fusion of historical temperature ocean data. The results showed that the overall performance of TD-LSTM was better than Support Vector Regression (SVR) and Multilayer Perceptron Regressor (MLPR).

Apart from dissolved oxygen and chlorophyll-a content, water temperature, other water quality (pH value, ammonia nitrogen, nitrites, nitrates) also influence the health of aquatic animals. To data these water quality factors studies on deep learning technology have been rarely reported before domestic and overseas.

2.9 Other Applications

Floating raft aquaculture has been widely distributed in some sea areas. Since visible light remote sensing images can’t obtain raft information accurately, synthetic aperture radar (SAR) images based on active imaging technology can accomplish the task well. Aiming at the problem of speckle noise pollution and single feature of marine remote sensing SAR images, Geng et al. [88] proposed a deep cooperative sparse coding network to extract feature from SAR images and perform target recognition automatically in marine floating raft aquaculture monitoring tasks. The proposed method extracts texture features and contour features after preprocessing. Then, the images were segmented by super pixel segmentation. Then the pixel features of each super pixel block are optimized to make the pixel features of the same super pixel block more similar and smoother. A deep cooperative sparse coding net-work was finally used to extract higher level features and perform the recognition task. The overall ac-curacy of the proposed method was about 98% and 89% in two data sets, respectively, which was better than SVM [89], SOMP [90], Sparse autoencoder and Lasso-Pooling [91]. The running speed was also fastest compared to other methods. The result proved that the network proposed in this study was effective and applicable in marine floating raft aquaculture monitoring tasks.

AUVs have increasingly been used to perform various tasks in underwater environments such as fish detection [44], jellyfish recognition [67] and fish classification [22]. However, there are few studies addressing vision-based obstacle avoidance in underwater environments. Gaya et al. [92] proposed CNN for automatic obstacle avoidance in underwater environments. The method used AUVs with a single monocular camera to capture images. Then a previously trained convolutional neural network was used to compute a transmission map. The trans-mission map was used to estimate the relative depth of an object. Then a direction of escape was found, and the signals of the robot was controlled. This study didn’t evaluate the method. This process was similar to autonomous cars. Deep reinforcement learning could be considered to be used in this study.

For robust grasp and manipulation of biological and deformable objects such as fish, it is still a challenging task in robotics due to complex scenarios. Dyrstad and Mathiassen [93] combined a deep 3D convolutional neural network with virtual reality technology to grasp virtual fish from 3D point clouds. They used domain randomization to generate large amounts of synthetic data. A deep 3D convolutional neural network (3DCNN) was applied to detect potential grasps and estimate the pose of the gripper. The network was able to guide a gripper to grasp virtual fish with success rate of 70%. However, the relatively low success rate wasn’t enough for a working system. This system would be implemented on a real-world robot and refine the neural network using reinforcement learning for better performance. The system may cut down a labor force not only, and but also may lighten workers' labor intensity in fishing industry.

There are many challenges in real underwater environment, such as changing light radiation, pose, water turbidity, background confusion, bio-fouling growth on the camera housing and moving aquatics. Deep learning technology is more suitable for these problems than conventional shallow machine learning algorithms and image processing techniques. Because the deep neural network is an imitation of human brain system, it can learn hierarchical representations of raw data automatically. CNN model is the most familiar and most used in aquaculture domain. Most research methods above use the CNN architecture or its variants due to its excellent ability to manipulate images. CNN is mainly used in image classification [22, 63, 69, 71] and detection tasks [53, 68]. In addition, CNNs also have great potential in processing various types of image data (i.e. RGB images, depth images, hyperspectral images, near infrared (NIR) images, aerial imagery and three-dimensional images). Even though RNNs have been explored less than CNNs, RNNs are currently the first choice of sequential information analysis. The application domains of such network architectures in aquaculture can be action recognition of aquatic animals [50], water quality prediction [78-79, 85-87] and sound classification [39]. As for the applications of autoencoders in aquaculture, autoencoders are mainly used for hyperspectral image processing [60] and they are also combined with other networks (i.e. CNN, LSTM) to improve the performance [58].

From another perspective, the experimental objects ranged from different species of fishes to shrimp, scallop, coral, jellyfish and water quality. Most papers (22 papers) target fish, while few works consider issues such as shrimp (3 papers), scallop (2 papers), scallop (2 papers), coral (2 papers), jellyfish (2 papers), aquatic macroinvertebrates (2 papers), phytoplankton (3 paper), water quality (5 papers), marine floating raft aquaculture monitoring (1 paper), obstacle avoidance in underwater environments (1 paper) and virtual fish grasp (1 paper). In addition, most studies involve object detection and classification (40 papers), while few works consider prediction (6 papers). Table 2 shows the applications of deep learning in aquaculture and the techniques used, in great detail.

Table 2. Applications of deep learning in aquaculture and the techniques used

Application	Data Description	Deep learning Techniques	Accuracy	Advantage	Limitation
Fish classification [22]	Fish Recognition Ground-Truth dataset	CNN	Classification accuracy achieve 98.64% for 23 fish species.	High accuracy	
Fish classification [24]	Underwater video imagery captured off the coast of Western Australia	CNN	Classification accuracy achieves 94.3% for 17 fish species.		Cannot satisfy the need of real-time processing
Grouper species classification [38]	The recorded sounds produced by Red hind, Black groupers, Yellowfin and Nassau groupers	CNN, LSTM	Classification accuracy achieves around 90% for 4 grouper species.		Need further performance improvement
Fish detection [44]	The data involves luminance-only underwater fish videos	A fusion of Flow Segmentation and Selective Search, CNN, MNMS	The average precision (AP) of detection improves by about 10% compared to non-fusion approach and about another 10% by using MNMS.	Automatically detect fish and avoid manual annotation	Single dataset
Classification of Zebrafish deformation [45]	The image data consist of two independent data sets with no drug treatment and with 100-nM and 200-nM camp-tothecin treatment.	CNN	The average accuracy is 92.8%, aver-age recall is 89.8%, aver-age precision is 93.4%, and average F score is 91.5%.	New application area	
Recognition of species of Triglidae family [34]	3 species: As-pitrigla cucu-lus, Cheli-donichthys lastoviza and Chelidonich-thys lucernus.	DBN	A high accuracy rate of 97.61%.	High accuracy	Need to extract the features in advance
Fish counting [46]	The dataset consists of 52 videos from 12 different conveyor belts	CNN	Results indicate the relative count error (for individual fish) ranges from 2% to 16%.	The paper is the first time to ap-ply deep learning technology to monitor discarded fish catch on fishing trawlers.	The counting accuracies of 3 of six belts only met the project requirements.

Table 2. Applications of deep learning in aquaculture and the techniques used (continue)

Application	Data Description	Deep learning Techniques	Accuracy	Advantage	Limitation
Fish behavior monitoring [50]	1000 verified video clips of three unusual behaviors and usual behaviors clusters.	RNN	The accuracies are 98.91%, 91.67% and 89.89% for detection, localization and recognition, respectively.	High accuracy	
Fish fillets defect detection [53]	Simultaneous acquire RGB and 3D fillet images using the same camera	CNN	The classification accuracy of CNN model achieves 100%.	High accuracy, high processing speed	
Organ disease research of shrimps [54]	The dataset available is comprised of 2,589 images, categorized by organs and diseases.	Zero-Shot Learning	No specific performance		No specific practice
Identification of soft shell shrimp [58]	The dataset includes 200 sound shrimp and 200 soft shell shrimp images.	SAENN	The proposed method achieves a mean accuracy more than 98.05%.	High accuracy	
Freshness dis-criminating of shrimp [60]	Near-Infrared Hyperspectral Imaging	Stacked auto-encoders (SAEs)-a logistic regression (LR)	The SAEs–LR achieves classification ac-curacy over 93% for freshness grade of shrimp.	Nondestructive, improve efficiency	
Scallop counting [61]	Sequential images are collected by an AUV off the east coast of the United States.	CNN	The performance achieves an average precision of 0.847.	High detection accuracy and real-time speed	Focus on simply identifying healthy scallops
Pearl classification [63]	The dataset contains 52500 multi-view images for 10500 pearls, each pearl has five images of top, left, right, main, and rear views.	MS-CNN	The proposed method achieves 92.14% and 91.24% test accuracies for two-class and seven-class classification tasks, respectively.	Save man-power and time, improve efficiency, high classification accuracy	
Sparse coral classification [64]	Moorea Labeled Corals (MLC) dataset and Atlantic Deep Sea(ADS) dataset.	CNN	The result of the method has best accuracy 66% using ADS dataset.		Low accuracy
Polyp activity estimation and monitoring [65]	Images are recorded at the fixed underwater observatory (FUO) LoVe, located in the north of Nor-way 22 km off the coast at a depth of 260m.	CNN	The accuracy at the test patch reaches a score of 96%.		Images annotations were placed manually
Jellyfish detection [67]	A UAV is used to capture the images of jellyfish on the surface of the sea.	CNN	The recognition accuracy reaches 80%.		The study only involved the 'Aurelia aurita'
Jellyfish detection [68]	Synthetic images and real images of the jellyfish	autoencoder-combined generative adversarial network, FCN	The results show an accuracy of 83.8% on real test dataset.	Outperform the result with 80.5% accuracy in Kim et al. [67], provide an available solution with limited dataset	
Classification of aquatic macroinvertebrates [69]	The dataset consists of 29 classes images of macroinvertebrates.	CNN	The classification accuracy reaches up to 85.64% for 29 macroinvertebrate classes.	Save man-power and time, improve efficiency	
Phytoplankton species and life-cycle stage identification [71]	The dataset consists of 46,797 bright-field and 46,797 Chl *a* fluorescence images of nine species.	CNN	Species identity and their respective life cycle stage could be predicted with a high accuracy of 97%.	Save time, improve efficiency, high accuracy	
Diatom classification [72]	The dataset with 69,350 samples of 80 diatom species	CNN	An overall accuracy of 99% is obtained.	High accuracy, new application area	
Trend prediction of red tide biomass [73]	Ship sampling data at high incidence of red tides are provided by various monitoring stations in Zhejiang Province.	A CRBM-DBN hybrid model combining CRBM model with DBN model	The prediction accuracy of the proposed method is 72.62%.	Stable, reliable, outperform than other methods (DBN, DAE, BP)	Single data source

Table 2. Applications of deep learning in aquaculture and the techniques used (continue)

Application	Data Description	Deep learning Techniques	Accuracy	Advantage	Limitation
Dissolved oxygen prediction [78]	Experimental data mainly include water temperature, pH value, dis-solved oxygen, wind speed, wind direction, solar radiation, air temperature, air humidity, atmospheric pressure, soil moisture and soil temperature.	PCA-LSTM	The MAE, MAPE and RMSE of the PCA-LSTM are 0.274, 0.089 and 0.147, respectively.	The prediction accuracy and generalization performance of PCA-LSTM are better than those of BPNN, PSO-BP, ELM and LSSVM.	
Dissolved oxygen prediction [79]	The dataset is measured in a shrimp pond by every 10 minutes one set for 20 consecutive days, including four water quality factors and four meteorological factors: dissolved oxy-gen (DO), water temperature (W_T), ammonia nitrogen content (Am), pH and atmospheric temperature (A_T), air humidity (Hu), atmospheric pressure (AP), and wind speed (WS).	Sparse auto-encoder and LSTM network	The MSE of SAE-LSTM is 0.0056, 0.0077and 0.0242, for 3h, 6h, 12h pre-diction, respectively.	The performance of SAE-LSTM surpasses those of LSTM and SAE-BPNN.	
Chlorophyll-a content prediction [85]	688 sequence data, which consist of 8-days observations	LSTM	The slightest test error was 0.04868 for the 1-day pre-diction task and 0.08015 4-days prediction task.		Obtained data need to be randomly shuffled
Prediction of harmful algal blooms [86]	The water quality data are measured weekly from 16 dammed pools on four major rivers in South Korea.	MLP, RNN, LSTM	The RMSE average of LSTM model is 16.09.	Prediction performance is better than OLS, MLS, RNN models.	There are some missing data values and the predicted results are not always accurate.
Temperature prediction [87]	Global Ocean Argo Grid Data Set (BOA_Argo) [94]	TD-LSTM network	The overall performance of TD-LSTM is the best.	Better than SVR and MLPR in multiple seas, shorter input sequence length	
Identification of marine raft breeding targets [88]	Artificial and real SAR re-mote sensing images in the Beidaihe sea area.	DCSCN	The overall accuracy reaches about 90%.	High accuracy and fast running speed	
Obstacle avoidance in underwater environments [92]	680 clear underwater images	CNN	The proposed approach can find free areas and to establish a direction of escape.	New application area	This study didn't evaluate the meth-od.
Grasping virtual fish [93]	The dataset consists of 76 000 example grasps of fish.	3DCNN	The network can guide a gripper to grasp virtual fish with success rate of 70%.		The relatively low success rate isn't enough for a working system.

3 Discussion

Here we will introduce the advantages and limitations of deep learning and the future trends and challenges in aquaculture domain. Table 3 summarized the advantages and limitations of deep learning in aquaculture.

Table 3. Advantages and limitations of deep learning in aquaculture

Advantages	
High accuracy	The classification accuracy for 16 fish species was 94.3% [24].
	The accuracy of CNN model for the defective cod fish fillets classification task achieved 100% [53].
	The phytoplankton species identification and their respective life cycle stage could be predicted with a high accuracy of 97% [71].
Fast	Process one fillet image in average 1.5s [53].
	The running speed of DCSCN is fastest com-pared to other methods (SVM, SOMP, SAE and Lasso-Pooling) [88].
Nondestructive	Nondestructive shrimp freshness detection systems [60].
	Automatic classification of soft-shell shrimp [58].
Economical and labor-saving	Discarded fish catch automatic monitoring on fishing trawlers [46].
	Pearl classification: two and seven classes [63].
	Automatic classification of aquatic macroinvertebrates [69].
Good generalization	Dehaze with images from a location and be used in a different location [43].
	Desensitize shape of blood spots [53].
Robust and reliable	The noise pollution, occlusion, low-contrast, blurring problem of fish detection [44].
	Real video data from 12 different conveyor belts [46].
Limitations	
Limited dataset	Only identify healthy scallops [61].
	Only ship sampling data for trend prediction of red tide biomass [73].
	Luminance-only underwater fish videos for fish detection [44].
Black-box problem	Cannot visualize the abnormal behaviors of fish [50].
Selection problem of appropriate architectures and parameters	LSTMs and CNNs for grouper species classification to compare their performances [38].
	The RMSE value of the LSTM model is the best at 700 epochs [86].

3.1 Advantages of Deep Learning in Aquaculture

Compared with the image processing technology and traditional machine learning methods, the most important advantage of deep learning methods is automatic feature extraction from raw data, reducing effort in feature engineering. The manual design process not only takes a great deal of time, but also inevitably introduces the human error. In addition, manual feature extractors often perform badly when target objects are too similar or the images are low-contrast in some detection/classification tasks. For example, for fish species classification task, human is not easy to design the features to differentiate the fishes due to similar characteristics. Moreover, the improvements in performance of the detection/classification/prediction problems were demonstrated in most surveyed works. The high accuracy and fast processing speed are both conducive to the extensive use of underwater robots.

A good generalization is another advantage of deep learning technology. The pre-trained models can be transferred to other similar fields, which improve the efficiency greatly and avoid the need of large volume data during the training process. And deep learning models can identify the unseen images on the training dataset, while traditional machine learning methods need continuous patching algorithms to address such issues.

Finally, deep learning approaches have nice robustness for the variations of occlusion, lighting, resolution, pose and background. For example, underwater conditions are usually complex, such as variations in lighting, pose, background, and water turbidity and features of fish are subtle. Conventional computer vision techniques do not perform well in such underwater conditions. Siddiqui et al. [24] used a pre-trained CNN and a cross-layer pooling algorithm for fine-grained fish species classification. The classification accuracy reached 94.3% for fish species from typical underwater video imagery.

3.2 Limitations of Deep Learning in Aquaculture

Deep learning needs a lot of data during the training process, while acquiring so much data is sometimes difficult to achieve in real life. especially aquaculture domain. For example, fishes' abnormal behavior data acquisition is difficult, and there is no strict discrimination between normal and abnormal behavior. Fishes' disease research remains a challenging issue due to the limited data. The underwater environment is so complex that the abnormal behavior and disease data of fish are harder to obtain. Besides, the existing publicly available datasets in aquaculture are too few. The common solutions to limited data include data augmentation, transfer learning, synthetic data and algorithm improvement. Data augmentation techniques use image processing techniques to increase sample data. Transfer learning uses the adjustment of similarly trained models to solve the problem of insufficient data. Some studies used synthetic data to train the model, then the real data was used to test the model. The synthetic data may be generated by human [95-96], domain randomization [93], GAN [68]. Algorithm improvement refers to increasing the amount of data by combining with other algorithms [53]. Besides, Mendieta and Romero [54] transferred text description into images to increase the training dataset. Apart from the number of training data, training data types will affect the result as well. Single training data type can cause bad robustness and low generalization ability.

A main challenge against deep learning is the black-box problem. Though deep learning methods get great performance in many problems, users know very little about how to achieve such good performance internally. However, it is not enough to simply produce good outcomes in some tasks. For example, the individual and colony behaviors of fish are connected to fishes' health conditions. These studies need to know the internal logical reasoning for medical treatments. A novel deconvolutional neural network (DeConv) has been proposed to visualize hierarchical representations for a specific image input of CNNs [97]. These visualizations give insight into the activity within the CNN model. Apart from the DeConv, Ishaq et al. [45] utilized ablation studies to observe how the CNN learned the discriminative features of fish deformations. The results revealed that the deformations of the head region rather than the visually apparent bent tail, were more important for good classification performance. At present, the techniques that visualize and understand the deep learning architectures are still in the early stages. More needs to be done to transform deep learning from the black-box into the white-box.

Deep learning architecture is so many that it is not easy to choose one appropriate architecture for the task at hand. Simultaneously, the researchers need to set many parameters such as the number of layers, weight initialization values, learning iterations and the learning rate simultaneously. The choice of deep learning architecture and parameters are all crucial to the results. Therefore, the good result is not promised because the choice of architecture and parameters is left up to human experts. To achieve the best performance, researchers always choose the deeper networks. It is true in theory that the deeper the deep networks are, the better the performance of the models. However, the real network is not as deep as possible because deeper layers may lead to a drastic increase in computational costs and training time. Through the hyper-parameter tuning mostly depends on expert experience at present, some hyper-parameter optimization algorithms have been proposed to improve automatic procedures, which include random search [98], Bayesian optimization with Gaussian process priors [99] and sequential model-based optimization [100]. These proposed optimization algorithms can reach better results than human expert-level optimization.

As mentioned above, although deep learning is a useful method in aquaculture, there are still some limitations, including insufficient datasets, the black-box problem, architecture and parameters selection problem. The common solutions to limited data include data augmentation, transfer learning, synthetic data and algorithm improvement. The DeConv and ablation study are feasible methods to solve the black-box problem of CNNs. In order to improve automatic procedures of choosing appropriate architecture and parameters, some hyper-parameter optimization algorithms have been proposed, including include random search, Bayesian optimization with Gaussian process priors and sequential model-based optimization.

3.3 Future Trends of Deep learning in Aquaculture

Incorporation of traditional deep learning architectures is a promising future trend in aquaculture. For example, Li et al. [79] combined SAE and LSTM network to improve the prediction accuracy of dissolved oxygen in aquaculture. The result showed that SAE-LSTM outperformed LSTM, BPNN and SAE-BPNN. When the performance of simple incorporation of traditional deep learning architectures equals or exceeds the well-designed network structure, the former is more popular.

Many machine learning and data mining algorithms perform well under a common assumption: the training and test data are in the same feature space and have the same distribution [101]. However, once the assumption is invalid, most models need to be rebuilt from scratch using new training data. The data in aquaculture is insufficient because the actual environments are too complex. Transfer learning is proposed as a new learning framework to address this problem, which uses the knowledge learned from an environment to help complete tasks in the new environment [102-103]. Transfer learning is often used to solve the problem of insufficient data volume in a specific field and improve the stability and generalization ability of the models. And it can save the training time and computing resources. What' more, the training results are not worse than the results of training from scratch. Based on these advantages, transfer learning will become a hot research direction. So far, transfer learning method has been widely used in many areas of aquaculture [24]. This is because in the aquaculture domain the datasets are limited, and it is challenging to train the network architectures from the scratch.

Another solution to insufficient dataset problem in aquaculture is GANs, which include two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G [104]. The generative model occupies a dominant position in unsupervised deep learning and can be used to capture high-order correlations of visible data without label information. Generated sample images are very sharp and clear, providing an available solution to limited dataset in some tasks. For example, Kim and Myung [68] combined autoencoder with generative adversarial network to generate synthetic images of the jellyfish. The designed classification network was trained with the synthetic image data and the results showed an accuracy of 83.8% on real test dataset. GAN has realized the synthesis of realistic images from text description [105]. For aquatic animals' disease research, fish classification, fish counting, fish behavior monitoring, GAN offers a possible solution to limited dataset. Because the datasets are limited in the field of aquaculture, GAN will become one of hot research directions in this field.

Reinforcement learning is receiving attention recently. Aquaculture is expected to benefit greatly from this network. Reinforcement learning leverages reward out-come signals resulting from actions and learns optimal policy in the end by maximizing expected re-wards. A successful example using reinforcement learning is AlphaGo, which defeated champion of World go. Reinforcement learning has been used for the planting of greenhouse. For example, Ban et al. [106] proposed the actor-critic reinforcement learning approach to control a nonlinear, complex and black-boxed artificial green-house environment simulator system. The model succeeded to maintain the environment for 200~350 hours which is enough for farmers to grow and harvest lettuce. Fish breeding by greenhouse has become one of culture models in recent years, which breaks through the constraint of half-year aquaculture model. The proposed approach in Ban et al. (2017) can be extended to aquaculture filed. Deep reinforcement learning combines the perception ability of deep learning with the decision-making ability of reinforcement learning in a common form and can realize direct control from original input to output through end-to-end learning [107-108]. At present, deep reinforcement learning technology has been widely used in games [109-111], robot control [112-114], parameter optimization [115-116], intelligent driving [112] and intelligent medical services. And it is considered as an important way towards artificial general intelligence. For the tasks in aquaculture, deep reinforcement learning is promising in the field of unmanned underwater vehicle, aquatic robots (i.e. picking robot, conveyance robot, sorting robot) and parameter optimization of greenhouse.

Multimodal deep learning [117], which learn features from multiple sources, is a promising future trend. Cross modality feature learning has been proved better than one modality (e.g., video) if multiple modalities (e.g., audio and video) are present at feature learning time. Aquaculture is expected to benefit greatly. For instance, fishes' growth relates to not only feeding, but also age, animal breed, weight, health condition, time, growth trajectory and pervious days feed quantity. Fishes' disease is also related to many factors, such as behavior, symptom, age, breed and environmental conditions. Aquaculture production correlates with many factors, such as aquaculture model, animal breed, feeding, weather, water quality, etc. In addition, for the environment monitoring task of greenhouse in aquaculture, the integration of sensor technology and multimodal deep learning has the potential to achieve good performance. There are a few studies about fish behavior monitoring. Fish behavior monitoring needs to collect and analyze not only motion data from motion sensors (i.e. speed sensors, acceleration sensors, position sensors) but also image data from video sensors. Multimodal deep learning exactly offers an available solution to solve this kind of problem. Though there is no the correlation report about the aquaculture application of multiple data types, some works have utilized multiple image types to perform their tasks. For instance, Misimi et al. [53] combined 3D and RGB-D images for segmentation of blood defects in cod fillets and calculation of gripper vectors for robotic processing. The 3D information was used to localize in 3D space the blood spots and to calculate the relevant gripper vectors. For example, fish behavior monitoring needs to collect and analyze not only motion data from special motion sensors (i.e. speed sensors, acceleration sensors, position sensors) but also image data from video sensors. Multimodal deep learning is exactly designed to solve this kind of problem,

Finally, the synergies of computer vision, deep learning and robotics will become one of future research directions in aquaculture. Deep learning has become an important tool in most computational vision tasks due to its great image processing ability. Its high accuracy, high-speed processing and good generalization and strong robustness make robots' practical application possible. For instance, Misimi et al. [53] proposed convolutional neural networks and SVM model for segmentation of blood spots and calculation of gripper vectors for robotic processing. The test classification accuracy of CNN model was 100% when the number of samples was 15327, which was better than SVM model (99%). The high classification accuracy in 3D space helped calculate the gripper vectors for robotic processing. In addition, the combination of deep learning technology and other technology also appear in other research papers. For example, Dyrstad and Mathiassen [93] combined robotic deep learning with virtual reality for grasp detection from 3D point clouds. They firstly utilized a deep 3D convolutional neural network to grasp fish in a virtual environment and domain randomization was used to generate a large training synthetic data set. The network was trained to guide a gripper to grasp virtual fish with success rates of 70%. The proposed method of this paper laid the groundwork for future implementation in a real-world world. Due to the complex processes and environments in aquaculture, deep learning technology need to combine other technologies to solve actual problems. Deep learning technology, Radio Frequency Identification (RFID) technology and breeding techniques are usually combined to count fish and identify parent fish in breeding procedure of aquaculture. Deep learning technology, computer vision and robotics are usually combined to perform underwater robot cleaning task and fishes' weight measurement task. For weighing each fish and counting fish tasks, a specific device is needed to hold a fish or several fish, and then relevant image data are collected as inputs of the deep learning models for analysis. Therefore, the synergies of computer vision, deep learning and robotics will become one of future research directions in aquaculture.

3.4 Challenges of Deep learning in Aquaculture

Though deep learning methods show good development potentialities in aquaculture, there are some challenges as well. The first challenge is the massive sample size challenge. Deep learning technology needs massive sample size, which is hard to achieve in aquaculture. One reason is that the data are not easy to obtain in aquaculture due to the complex environments, such as fish disease data, fish behavior data, fish weight data and fry quantity data. For example, different species and different environments would lead to different diseases, and there are also differences in individual performance characteristics. And many diseases (i.e. parasitic diseases) lead to death without any unusual symptom. Another reason is that there are not many public databases in aquaculture. Therefore, it's difficult to obtain massive disease sample size in aquaculture. The second challenge is complex data challenge. The data from a variety of sources may be required for some tasks in aquaculture. For example, fish behavior monitoring needs to collect and analyze not only motion data from special motion sensors (i.e. speed sensors, acceleration sensors, position sensors) but also image data from video sensors. Multimodal deep learning is designed to solve this kind of problem, but it's still not mature yet. The third challenge is dependent furniture challenge. It may need specific furniture in some specific tasks of aquaculture. For example, weighing each fish and counting fish before selling fish is usually necessary. A specific device is needed to hold a fish or several fish, and then relevant image data are collected as inputs of the deep learning models for analysis. To handle these challenges, the deep learning area still needs continuous studies from the basic theory to the practical application in aquaculture.

4 Conclusion

In this paper, we provided an extensive review of aquaculture research applying deep learning in terms of fish, shrimp, scallop, coral, jellyfish, aquatic macroinvertebrates, phytoplankton, water quality and others.

We further discussed the advantages, limitations and future trends and challenges of deep learning in aquaculture. We found that deep learning offered better performance than traditional machine learning methods and image processing techniques in most areas of aquaculture. However, there remain many potential challenges, including limited dataset, the black-box problem, selection of the deep learning architecture and parameters, lack of theoretical support and reasoning ability and weak unsupervised learning ability.

Moreover, to fully exploit the capabilities of deep learning in aquaculture, incorporation of traditional deep learning architectures, transfer learning, deep reinforcement learning, generative adversarial network and multimodal deep learning require further study. And the synergies of computer vision, deep learning and robotics will become a promising avenue for the future of aquaculture applications. We hope this review can provide valuable insight for application of deep learning to advance aquaculture in future research.

Acknowledgements

This work is supported by Beijing Natural Science Foundation (Grant No. 4192023).

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