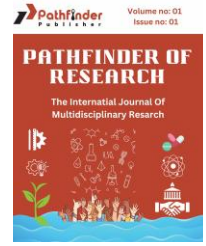
Journal homepage: https://pathfinderpub.com/index.php/pathfinder-of-research

Pathfinder of Research

ISSN (3007-3863), Vol. 2, Issue 3, December 2024



Original Research

Advancing Fish Farming Through Deep Learning: Applications, Opportunities, Challenges, and Future Directions

Bayazid Hossain [1], Atiqur Rahman Sunny [2*], Md. Mahfujur Rahman Nayeem Gazi [3], Anna Rani Das [4], Roby Mohajon [1], Abu Talha Haque Miah [1], Md Nasir Uddin Rana [5]

[1] Department of Electrical and Electronic Engineering, Barishal Engineering College, Barishal-8202, Bangladesh
[2] Pathfinder Research & Consultancy Center, USA
[3] Department of Electrical and Electronic Engineering, Islamic University, Kushtia 7003, Bangladesh.
[4]Department of Fisheries, Bogura, Bangladesh
[5] Department of Computer Science, Monroe University, New Rochelle, New York, USA

* Corresponding author: atiksunny@yahoo.com
https://doi.org/10.69937/pf.por.2.3.39

ARTICLE INFO
Article History:
Received: 17 October 2024
Accepted: 12 December 2024
Online: 14 December 2024

Keywords
Deep learning, Fish farming, Machine learning, Challenges, Opportunities

ABSTRACT
Deep learning (DL) has changed aquaculture by offering automated solutions for species identification, health assessment, biomass calculation, feeding optimization, and water quality forecasting. Conventional aquaculture encounters obstacles like ineffective resource management, disease epidemics, and environmental deterioration; nevertheless, deep learning applications provide intelligent decision-making skills that improve sustainability and economic feasibility. This study carefully looks at 41 peer-reviewed papers from 2015 to 2024 to find out how useful deep learning is in aquaculture. It focuses on main AI models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). The results indicate that AI-driven solutions boost fish health evaluations, optimize feeding strategies, and improve water quality monitoring, hence minimizing waste and augmenting production efficiency. Nonetheless, obstacles like substantial computing demands, dataset restrictions, and regulatory limits impede extensive implementation. Comparative assessments demonstrate that deep learning models surpass conventional aquaculture methods in precision and prediction efficacy. In the future, researchers should investigate new AI technologies like federated learning, edge computing, and AI-integrated robotics to make deep learning easier to use and more scalable for aquaculture applications. By surmounting these obstacles and utilizing advanced AI technology, aquaculture may evolve into a more sustainable, efficient, and intelligent sector.

1. Introduction

Aquaculture is a vital sector for global food security, providing a sustainable response to the rising demand for seafood while reducing strain on wild fish stocks. Conventional fish farming systems frequently encounter obstacles, such as inefficiencies, many disease outbreaks, and environmental issues. The implementation of sophisticated artificial intelligence (AI), particularly deep learning (DL) technologies, has significantly enhanced the potential for intelligent aquaculture. Employing these strategies, automated data-driven insights improve monitoring, management, and decision-making processes **(Liakos et al., 2018)**. Deep learning (DL) is a subset of machine learning. Deep learning utilized neural networks, including many layers. These layers facilitate models that handle extensive and intricate information, extracting significant patterns from photos, videos, and sensor data. In aquaculture, DL is used to identify species, check on fish health, study behavior, automate feeding, estimate biomass, keep an eye on water quality, and set up robotic systems that can work on their own. All these things improve sustainability and economic viability **(Najafabadi et al., 2015).** By utilizing AI driven solutions, aqua culturists may improve production, promote fish health, decrease financial losses through reduced maintenance costs, and optimize resource management for long-term sustainability in the business.

The rapid depletion of the world's fish supply owing to overfishing and climate change has prompted a transition toward sustainable aquaculture **(Melnychuk et al., 2017; Alam et al., 2023)**. Despite its potential to meet increasing seafood demands, conventional aquaculture has several obstacles, including excessive feed consumption, poor water quality management, and heightened disease vulnerability, resulting in financial losses and environmental damage. Sustainable aquaculture aims to address these difficulties by employing effective resource utilization techniques, eliminating waste, and decreasing the environmental impact of fish farming operations **(Rahman et al., 2024)**. Deep learning significantly enhances sustainable aquaculture methods through the implementation of sophisticated monitoring and predictive analytics. Utilizing AI and deep learning technology for picture and video identification may identify fish behavior, immediately detect diseases, and improve feeding schedules, therefore reducing feed waste and enhancing fish health. Furthermore, predictive deep learning models provide real-time environmental assessments, enabling fish cultivators to anticipate risks and implement preventive measures, thus enhancing long-term sustainability **(Thrall et al., 2018; Sunny et al., 2018).**

The effective integration of deep learning technology in aquaculture has transformed the sector by enhancing real-time monitoring, autonomous decision-making, and precise predictive modeling. Deep learning technologies, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are used a lot in aquaculture to sort fish into groups based on their behavior and check on their health **(Sun et al., 2018).** Moreover, IoT-based deep learning models have the capability for continuous water quality monitoring, hence providing ideal aquatic conditions for sustainable fish maintenance **(Hu et al., 2015)**. In aquaculture, AI-driven automated feeding systems represent the primary application of deep learning technology. Deep learning models assess fish movement patterns and eating behaviors to ascertain the ideal quantity and time of feed, minimizing overfeeding, averting water pollution, and enhancing feed conversion efficiency **(Saberioon et al., 2017)**. Furthermore, sophisticated technologies such as transfer learning and Generative Adversarial Networks (GANs) are assisting in enhancing the flexibility of deep learning models for diverse fish species and aquaculture situations **(Ashakin et al., 2024).**

2. Research Methodology

2.1 Synthesis and Curation of Literature

A thorough literature search was performed across several academic databases, including Web of Science, Scopus, IEEE Xplore, SpringerLink, and Google Scholar, to collect peer-reviewed papers, conference proceedings, and technical reports published from 2015 to 2024. Keywords including deep learning in aquaculture, intelligent fish farming, machine learning in fisheries, and AI in sustainable aquaculture were employed to guarantee focused retrieval. The criteria for selection included studies that looked at deep learning applications in aquaculture, such as identifying species, monitoring health, estimating biomass, feeding optimization, and predicting water quality **(Liakos et al., 2018; Najafabadi et al., 2015).** We only considered publications published in indexed journals (Q1-Q3) or prestigious conferences, excluding research lacking in technical rigor or experimental validation.

2.2 Thematic Analysis and Categorization

The research that was looked at broke down into six main uses of deep learning in aquaculture: identifying live fish, identifying species, studying behavior, estimating size and biomass, making decisions about what to feed, and predicting water quality. Deep learning models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) were used in each category, along with data sources like image datasets, sensor data, and IoT-based monitoring systems **(Saberioon et al., 2017).** The efficacy of these models was evaluated using accuracy, precision, recall, mean squared error (MSE), and root mean square error (RMSE) **(Sun et al., 2018).**

2.3 Comparative Assessment and Performance Evaluation

To find out how useful deep learning models are, they were compared based on how well they classify things, how quickly they can be computed, how well they can be scaled, and how well they can be used in real life. A comparison was made between traditional fish farming practices and AI-driven alternatives, emphasizing the benefits in decision-making, early illness diagnosis, and resource management **(Rahman et al., 2024).** The study looked at how better AI models were at classifying images and making predictions compared to more traditional image processing and machine learning methods.

2.4 Challenges and Prospective Pathways

This review found big issues with using deep learning in aquaculture, like high computing costs, limited datasets, and problems with how well models work in different aquatic settings **(Zhou et al., 2018).** Regulatory issues, including data privacy and security in AI-driven aquaculture, were addressed, alongside the necessity for defined standards for AI integration in fish farming. In the future, researchers will focus on improving the efficiency of AI models through federated learning, processing in real time through edge computing, and putting AI into robotic systems to run aquaculture operations automatically **(Hu et al., 2015).** By tackling these difficulties, deep learning can substantially improve sustainable fish farming and aquaculture management.

3. Results and Discussion

3.Concepts of Deep Learning

3.1 Terminology and Concepts in Deep Learning

In conjunction with big data and high-performance computing, machine learning (ML) has facilitated novel approaches for interpreting, measuring, and understanding data-intensive processes. Machine Learning (ML) is a scientific field focused on empowering machines to learn autonomously without much programming **(Samuel 1959; Uriondo et al. 2024)**. Deng and Yu (2014) assert that deep learning is a subset of machine learning and a representation learning technique based on artificial neural networks. Deep learning (DL) is a subset of machine learning applicable to many artificial intelligence applications, albeit not universally **(Goodfellow et al., 2016; Saufi et al., 2019).**

Deep learning addresses the core challenge of representation learning by enabling computers to formulate intricate concepts from simpler components **(LeCun et al., 2015; Bronstein et al., 2017)**. A deep learning system might amalgamate fundamental concepts to represent the notion of a fish. The functions linking an item to a pixel array are rather complex. Direct programming appears incapable of learning or evaluating such a mapping. DL deconstructs this complex mapping into a hierarchical arrangement of simpler mappings to resolve this issue **(DeFilippo et al., 2023).** The exposed layer inputs data into a series of hidden layers that gradually extract abstract information. The first layer may swiftly ascertain if a certain pixel represents an edge by evaluating the luminance of adjacent pixels. The second concealed layer then identifies clusters of edges that resemble elongated forms and angles. The third hidden layer can identify a certain arrangement of corners and contours that represent a whole area of an object. Finally, it is feasible to distinguish the various objects **(Zeiler & Fergus 2014; Goodfellow et al., 2016).**

3.2 Educational Models and Activities

A deep learning strategy often involves a learning process aimed at acquiring "experience" from samples to facilitate task performance. Deep learning approaches into supervised learning and unsupervised learning. In supervised learning, labeled samples of inputs and their matching outputs are utilized to present data. The objective is to establish mapping rules from input to output. Two prevalent model designs are the recurrent neural network (RNN) and the convolutional neural network (CNN). Convolutional Neural Networks (CNNs), inspired by the human visual nervous system, excel in image processing **(Litjens et al., 2017; Saufi et al., 2019; Uriondo et al., 2024)**, whereas Recurrent Neural Networks (RNNs) are proficient in handling sequential data.

In unsupervised learning **(Geoffrey & Hinton 1999)**, the model looks for patterns it hasn't seen before in a dataset that hasn't been labeled. It does this without any help from a person. Generative adversarial networks (GANs) represent one of the most promising techniques for unsupervised learning. A GAN might be able to make good results by using reciprocal game learning between at least two framework modules, such as a discriminative model and a generative model. The early deep learning models established the basis for other improved or altered models, such as long short-term memory (LSTM) and region convolutional neural network (R-CNN) models. Deep learning employs end-to-end optimization to integrate feature learning and model development into a unified model. In traditional machine learning, each component is developed sequentially, with feature extraction and model creation executed individually. Unlike traditional machine learning, deep learning uses a deep hierarchical structure that lets function combinations model nonlinear relationships **(Rubbens et al., 2023)** instead of surface-level structures. The advantages of deep learning become increasingly evident when handling substantial volumes of data. Hierarchical learning and the extraction of different levels of complex data abstractions in deep learning make big data analytics tasks easier. This is especially true when working with large datasets, tagging data, retrieving information, or doing discriminative tasks like prediction and classification **(Najafabadi et al., 2015).** Hierarchical architectural learning systems have exhibited superior performance in several engineering applications **(Poggio & Smale 2003; Mhaskar & Poggio 2016).** In fisheries management, deep learning does inductive analysis, acquires information from samples, and finally formulates recommendations to inform management decisions. The primary issue with deep learning is hallucinations. Overfitting and overlearning are two additional modes of failure for neural networks. Moreover, by introducing little alterations to their inputs, neural networks may be misled into producing completely different outputs **(Moosavi-Dezfooli et al., 2016; Belthangady & Royer 2019).**

3.3 Applications of Deep Learning in Intelligent Aquaculture

This review includes forty-one publications on deep learning and intelligent aquaculture. The relevant applications may be categorized into six distinct areas: live fish identification, species classification, behavioral analysis, feeding decisions, size or biomass computation, and water quality prediction. Species taxonomy and live fish identification are the foremost domains. Notably, all of these papers three from 2016, three from 2017, twelve from 2018, fifteen from 2019, and eight from 2020 (up to May 2020) were published in 2016 or subsequently. This indicates that deep learning has progressed rapidly since 2016. The bulk of papers employ image processing alongside sound identification and water quality forecasting. Moreover, a limited number of research studies investigate lobsters or other aquatic animals, despite the predominant focus of the bulk of publications on fish **(Chowdhury et al., 2021).**

3.3.1 Identification of Living Fish

The advancement of intelligent breeding management systems relies on the capacity to precisely and autonomously identify live fish, hence providing data support for enhanced production management. Machine vision enables long-term, nondestructive, noncontact observation at a low cost **(Zhou et al., 2018b; Hartill et al., 2020).** Nevertheless, the visuals seen in aquaculture provide several challenges for image and video analysis. Light, noise, and water turbidity can significantly diminish image quality, resulting in reduced contrast and resolution **(Zhou et al., 2017a)**. Secondly, the behavior of fish may lead to distortions, deformations, occlusion, overlapping, and other adverse phenomena due to their status as uncontrolled targets that swim freely **(Zhou et al., 2017b, Sunny et al., 2020).** These difficulties adversely affect most current image analysis methodologies **(Qin et al. 2016; Sun et al., 2018).**

Despite extensive research addressing the aforementioned issues, the predominant focus has been on the extraction of traditional low-level features, which generally encompass minute details in an image such as feature points, colors, textures, contours, and notable shapes **(White et al., 2006; Yao & Odobez 2007)**. Approaches reliant on these characteristics often yield suboptimal outcomes in practical applications. Deep learning (DL) employs multilevel data representations that vary from low to high levels. High-level features are derived from low-level features and include substantial semantic information that aids in the identification and detection of objects or targets inside an image. Convolutional neural networks often utilize both types of features: low-level features are acquired by the initial layers, and high-level features are obtained by the end layers. The difficulties may be addressed by this technique **(Zheng et al., 2017; Sun et al., 2018).** Most people use deep learning to identify whether an object is a fish, making it easier to identify live fish **(Sunny et al., 2021b; Rourke et al., 2022).** Deep learning can serve as an effective machine vision solution in the contemporary era, characterized by the ease of collecting extensive visual data. To explore efficient and accurate methodologies, it is beneficial to examine the performance capabilities achievable through the integration of deep learning with machine vision. The principal disadvantage of deep learning is the requirement for a considerable amount of labeled training data, which demands significant work and time to obtain and annotate an adequate number of pictures. The caliber of the annotations and training samples influences the recognition outcome.

3.3.2 Taxonomy of Species

Approximately 33,000 distinct species of fish exist **(Oosting et al., 2019, Chowdhury et al., 2020).** Species categorization facilitates aquaculture production management, yield forecasting, and ecosystem surveillance **(Alcaraz et al., 2015; dos Santos & Gonçalves 2019)**. Visual attributes such as dimensions, morphology, and pigmentation are commonly employed to distinguish various fish species **(Hu et al., 2012; dos Santos & Gončálves 2019**). Precisely categorizing fish species is challenging due to differences in light intensity, fish movement, and morphological and pattern similarities among species. Deep learning models can acquire unique visual characteristics of species that are impervious to environmental changes and modifications. during the utilization of DL. An object detection module first generates many patch proposals for each frame F in an underwater video presented as an examination. We generate a label distribution vector by inputting each patch into the classifier. Sun et al. (2018) assert that the tags of these patches correspond to the highest likelihood. However, significant opportunities for enhancement in the precision of same-species classification persist due to various interferences and restricted sample sizes. Classifying similar fish and those of the same species remains challenging, as most contemporary fish classification methods are designed to distinguish between specimens exhibiting significant variations in body size or morphology **(dos Santos & Goncálves 2019; Sunny et al., 2021a).**

3.3.3 Behavioral Analysis

Fish have various behavioral reactions to alterations in environmental circumstances due to their sensitivity to these changes **(Flück et al., 2021)**. Moreover, behavior serves as a valuable indicator for both harvesting and fish well-being (Zion 2012). Relevant behavioral monitoring, especially for anomalous behaviors, can achieve a nondestructive comprehension and early warning of fish conditions **(Rillahan et al., 2011).** Real-time monitoring of fish behavior is essential for assessing their condition and informing feeding and capture strategies **(Yu et al., 2022).** Fish show behavior through a series of temporally connected events that possess certain continuity. Images captured prior to and after the activity will no longer pertain to methods that discern it from an individual image. To effectively capture action significance, it is advisable to utilize time-series data from the preceding and subsequent frames in a movie. Deep learning algorithms exhibit significant proficiency in visual pattern identification. RNNs have the capacity to adeptly address the previously described problem, mostly because of their robust modeling proficiency for sequential data **(Schmidhuber, 2015).** According to Zhao et al. (2018a), they came up with a new way to use a recurrent neural network and an altered motion impact map to find, identify, and report any strange behaviors in a school of fish in intensive aquaculture. Obstructions to behavior analysis in fish classification via deep learning include crossing, overlapping, and blocking caused by free-swimming fish **(Zhao et al., 2018a; Romero-Ferrero et al., 2019)** and subpar environmental imagery **(Zhou et al., 2019)**; thus, these challenges necessitate resolution in the future.

3.3.4 Estimating Dimensions or Biomass

In operating a fish farm, it is essential to continuously assess fish parameters such as abundance, number, size, and weight **(Francá Albuquerque et al., 2019).** Scientific fisheries management and conservation strategies for sustainable fish production rely on quantitative assessments of fish biomass **(Melnychuk et al., 2017; Saberioon & Cısar 2018; Li et al., 2019).** Fish exhibit sensitivity and navigate freely in surroundings characterized by fluctuating visibility, illumination, and stability, complicating the estimation of fish biomass without human intervention **(Li et al., 2019).** Recent applications of deep learning to fisheries research provide promising potential for large sampling in intelligent fish farming. Deep learning combined with machine vision can enhance the precision of assessing fish morphological characteristics such as length, breadth, weight, and area. Semi supervised and supervised applications are the predominant category of published applications **(Marini et al., 2018).** A vital element of fisheries assessment models is the age distribution of a fish school. We currently use a method that requires a lot of work and skill to figure out the age breakdown of fish schools. This method involves manually judging the age of otoliths. We can achieve target identification by predicting fish ages from otolith photos using a pretrained convolutional neural network in a deep learning approach. The accuracy is markedly superior and comparable to that achieved by human experts **(Moen et al., 2018).** We routinely assess fish biomass using sonar and optical imaging techniques. A "daytime" image may be generated from a sonar image and a corresponding night vision camera image by employing a deep learning system to autonomously discern the conversion connection between sonar and optical images. This approach is effective for enumerating fish **(Terayama et al., 2019).**

3.3.5 Decision-making regarding feeding

Fish feeding levels in intensive aquaculture directly influence breeding costs and output efficiency **(Chen et al., 2019).** For some fish species, feed costs constitute more than 60% of total production expenditures **(Wu et al., 2015; Føre et al., 2016; de Verdal et al., 2017)**. Consequently, overfeeding will diminish production efficiency, while insufficient feeding may adversely affect fish development. Excessive feeding not only diminishes feed conversion efficiency but also contaminates the environment with residual bait **(Zhou et al., 2018a)**. Consequently, optimizing the feeding process can produce substantial cost advantages **(Zhou et al., 2018c).** Experience and fundamental time constraints have always significantly influenced feeding decisions **(Liu et al., 2014b).** Presently, image analysis has been the predominant emphasis of most research on utilizing deep learning for feeding judgments. A sophisticated feeding strategy that considers fish behavior may be developed using machine vision. By halting the feeding process at more appropriate intervals, such a system can conserve unnecessary labor and improve fish welfare **(Zhou et al., 2018a; Qiao et al., 2021).** Fish feeding may also be directed using a rudimentary classification system for feeding intensity. The parameters of fish feeding intensity may be accurately assessed by integrating CNN and machine vision **(Zhou et al., 2019).** The primary emphasis of the research was on images. Nonetheless, several factors affect fish eating **(Sun et al., 2016);** hence, dependence exclusively on pictures is insufficient. To enhance future feeding decisions, it is imperative to include more information, including environmental metrics and fish physiological data.

3.3.6 Monitoring Water Quality

To identify anomalous events, prevent disease, and mitigate related risks to fish, it is essential to predict fluctuations in water quality parameters **(Hu et al., 2015; Rahman et al., 2024).** The aquatic environment in real-world aquaculture is defined by several interrelated elements, rendering the prediction process very challenging **(Liu et al., 2014a).** Conventional machine learning prediction models exhibit a lack of resilience when applied to huge data, resulting in diminished generalizability and long-term modeling efficacy. Furthermore, they cannot precisely encapsulate the essential characteristics of the data **(Ta & Wei 2018; Liu et al., 2019)**. Conversely, deep learning has robust nonlinear approximation, self-learning, and generalization capacities. Deep learning-based prediction methodologies have surged in prominence in recent years **(Roux & Bengio, 2008)**. Nonetheless, only short-term water quality forecasts have demonstrated favorable results utilizing most contemporary methodologies. Recent years have seen an increased focus on long-term projections among scholars **(Ashakin et al., 2024).** Establishing the spatiotemporal connections between water quality and external factors is crucial for long-term forecasting. As a result, spatiotemporal models such as RNNs and LSTM networks are highly favored **(Hu et al., 2019).** An attention-based RNN model is better at learning than other methods for both short- and long-term predictions of dissolved oxygen. It also makes a clear and useful representation of how time and space interact **(Liu et al., 2019).** These models may be perpetually enhanced during the forecasting process to augment their predictive accuracies **(Deng et al., 2019).** Time significantly influences the prediction of dissolved oxygen and other water quality parameters. Attention-enabled deep learning models, including LSTM, DBN, and others, can proficiently extract insights from temporal sequence data and yield commendable results. Consequently, a pivotal research focus for water quality prediction tasks will be the application of deep learning models to mitigate or reduce the adverse impacts of uncertainty factors on predictive results.

3.4 Comprehensive Performance and Technical Specifications

The two fundamental elements of AI are data and algorithms **(Thrall et al. 2018)**. Each of these components is essential for the success of AI.

3.4.1 The data

An annotated data set is crucial to ensure a model's success in deep learning (Zhuang et al. 2019). Nonetheless, issues related to both quantity and quality often affect the generation of data sets **(Ifty et al., 2024)**. Preparing images through preprocessing and/or augmentation typically requires effort before any photographs or specific attributes may serve as input to a deep learning model. Modifying the picture dimensions to conform to the requirements of the deep learning model used is the predominant preprocessing method **(Siddiqui et al., 2017; Sun et al., 2018)**. Moreover, emphasizing the regions of interest **(Wang et al., 2017; Zhao et al., 2018b)** or streamlining picture annotation by background reduction, foreground pixel extraction, and image denoising enhancement **(Qin et al., 2016; Siddiqui et al., 2017; Zhao et al., 2018b)** might facilitate the learning process.

Additionally, some researchers have utilized pre-trained deep learning models to classify fish directly, thereby avoiding the necessity of collecting extensive annotated data to address the constraints provided by the lack of such data **(Ifty et al., 2023)**. This technique is mostly suitable for theoretical algorithm research because of its several limitations, including negative transfer **(Pan & Yang 2010)**, challenges in learning from holistic pictures **(Sun et al., 2019; Sazzad et al., 2023)**, and difficulties in satisfactory implementation for specific applications.

3.4.2 The Algorithm

1. Models. A multitude of CNN models remains the most prevalent from a technical standpoint (29 publications, 71%). Nevertheless, two of the analyzed studies utilize a GAN, three an RNN, two an LSTM, two a CNN combined with an LSTM, and two a DBN alongside YOLO, respectively. It is known that some CNN models work with output-layer classifiers, like Softmax

(Naddaf-Sh et al., 2018; Zhao et al., 2018b) or SVM mixed with Softmax **(Qin et al., 2016; Sun et al., 2018).**

2. Structures. TensorFlow and Caffe are the preeminent frameworks in use. Caffe has a model that has already been trained and can be easily improved through transfer learning. This may be one reason why it is so widely used (Bahrampour et al., 2015). Combining deep learning with transfer learning reduces the need for a lot of data and saves a lot of training time. This is useful for both business and experimental research **(Ifty et al.,2023b Ashakin, et al., 2024).** Numerous diverse deep learning frameworks and datasets are readily accessible for client utilization. The PyTorch framework has been extensively utilized in recent literature, particularly because of its strong support for graphics processing units (GPUs) **(Ketkar 2017; Liu et al., 2019).** A lot of the research in this paper (9/41) uses transfer learning, which is the use of existing knowledge from similar tasks or domains to make model learning more efficient **(Siddiqui et al., 2017; Levy et al., 2018; Sun et al., 2018)**. The most prevalent transfer learning approach is utilizing pretrained deep learning models that have been trained on analogous datasets with different categories. Afterwards, Lu et al. (2015) adapt these models to tackle specific issues and datasets. The network is initially trained with the labeled dataset from the source job. Subsequently, the model's training parameters are implemented for the designated tasks **(Oquab et al., 2014; Sun et al., 2018; Sazzad et al., 2024).**

3. Model inputs, the predominant inputs for the model are images, while several studies use fish vocalizations and water quality metrics (34, 83%). This case illustrates the significant advantage that deep learning offers in data processing, especially in image processing. The inputs include public datasets like ImageNet, Fish4Knowledge (F4K), and fish datasets from Croatia and Queensland University of Technology (QUT). Supplementary data sets comprise information collected and produced in situ or obtained from internet search engines such as Google **(Meng et al., 2018; Naddaf-Sh et al., 2018)**. Using optical sensors, machine vision, and deep learning systems together could lead to faster, cheaper, and less invasive ways to check the quality of aquaculture products both in situ and after they have been harvested **(Saberioon et al., 2017).** Nonetheless, these data sets typically encompass substantial amounts of information, irrespective of their format, whether it is text, audio, or image/video data **(Begum et al., 2022; Rahman et al., 2024).** When there is minimal differentiation between adjacent classes or when the task at hand is challenging, extensive datasets are essential.

4. Results of the model, the categorization models yield between four and sixteen distinct classes. One research study examines images of sixteen distinct species of fish, and another analyzes audio recordings of four different fish species. Thirteen papers focused on identifying live fish, with results related to both fish and non-fish; seven papers looked at size or biomass; two papers measured how much fish ate; six papers predicted water quality; and five papers looked at behavior. The parameters for identification, classification, and biomass calculation derived from these classification models are, however, somewhat confusing from a technical perspective. All models in these papers possess identical input and output classes. The model selects the class

with the highest output probability for each input as the projected class. Each output comprises a collection of probabilities indicating the likelihood of each input belonging to each class.

3.5 Comprehensive Performance and Evaluation Measurements

3.5.1 Performance Evaluation Measurements

Table 1 includes numerous indices used in the literature to evaluate model performance. Prevalent machine learning assessment measures such as accuracy and precision are employed in most identification and classification research **(Qin et al., 2016; Siddiqui et al., 2017).** Metrics such as the miss ratio (MR) are utilized in monitoring behavioral trajectories **(Wang et al., 2017; Xu & Cheng, 2017)**. Additional metrics such as the mean absolute percentage error (MAPE) and root mean square error (RMSE) are utilized for forecasting water quality **(Liu et al., 2019).** Moreover, when high real-time performance is required, a program's execution speed is a critical performance indicator **(Zhou et al., 2017a; Villon et al., 2018).** Evaluating models predicated on a solitary parameter lacks scientific rigor, as various studies utilize distinct models, input data, hardware configurations, and parameters **(Tripathi & Maktedar, 2019).** Generally, most studies utilizing accuracy as a performance evaluation parameter indicate results over 90%, with some nearing 100% **(Romero-Ferrero et al., 2019; Banan et al., 2020)**, implying the efficacy of these techniques. The advantages of deep learning models are evidenced by the highest results recorded in research utilizing precision and recall as evaluation metrics, achieving 99.68% and 99.45%, respectively.

3.5.2 Performance Comparisons with Alternative Methods

The examination of parallels between deep learning and other contemporary approaches is essential. We have developed seven deep learning models using audio and water quality data, but most deep learning approaches focus on image analysis. These findings indicate that deep learning can handle more than just photos in intelligent aquaculture. A deep learning model is only superior to other comparison models when utilized for the same task and dataset.

Table 1 DL models Performance evaluation indexes

Performance evaluation index	**Description**
Accurateness	Accurateness is the proportion of the number of properly expected fish to the total number of predicted samples
Accuracy	In the ground truth, the proportion of appropriately identified fish
Memory	In the total identified objects, the proportion of appropriately identified fish
Speed	Algorithm running time
Connection overunion (COU)	The ideal scenario is complete overlap. COU is the intersection ratio between applicant area and ground truth area.
Incorrect positive rate (IPR)	IPR is the ratio of negative instances divided into positive classes to all negative instances
Mean squared	The mean squared error is the expected value of the square of the

error (MSE)	difference between the parameter estimate and the true value
Average ratio of variation	The standard deviation divided by the mean. The degree of dispersion between two sets of data is reflected in the average ratio of variation.
Primarily traced paths	Proportion of ground truth that is accurately tracked for longer than 80% of the time. Greater values are preferable.
Trajectories that were mostly lost	% of ground truth cases that were accurately tracked for less than 20% of their total length. Smaller values are preferable.
Pieces	Percentage of trajectories that were accurately tracked at more than 20% of their length but less than 80%
Switch of ID	A resulting trajectory's average total number of times it swaps its matching ground truth identity with another trajectory is smaller the better.
Ratio of mis	The proportion of fish that are not shown in every frame.
The ratio of errors	Percentage of fish that were incorrectly identified across all frames.
Error root mean square	The square root of mean square error is the error root mean square.

CNN models are 18.5% more accurate than SVM models at identifying fish **(Qin et al., 2016),** 41.13% more accurate than Gabor filters and similar feature extraction methods, and 19.54% more accurate than manual extraction and linear discriminant analysis (LDA) **(Sun et al., 2018)**. Moreover, it has been established that a CNN model surpasses id Tracker **(Wang et al., 2017).** The accuracy of a CNN model was shown to be superior (95.7%); **(Villon et al., 2018; Chowdhury et al., 2022; Hasan et al., 2024)** compared to that of human experts (89.3%). In Moen et al. (2018), a convolutional neural network surpassed human experts in assessing the age of the fish population. The acquired mean coefficient of variation (CV) of 8.89% is markedly lower than the stated mean CV of human readings. The accessibility of data sets in these places, along with the unique characteristics of fish and other contextual aspects, may be the underlying reason for this. When it came to putting feed intensity into groups, a CNN model did 6.25% better than a backpropagation neural network (BPNN). In comparison to traditional manual feature extraction methods such as FIFFB and SIFFB, the evaluation metrics of the CNN model showed a shown enhancement **(Zhou et al., 2017b; Zhou et al., 2019).** Also, the water quality prediction results show that LSTM and attention-based RNN models are more accurate than BPNN models, Holt-Winters forecasting, and support vector regression (SVR) algorithms that use either a linear function kernel (SVR-linear) or a radial basis function kernel (SVR-RBF) **(Ta & Wei, 2018; Liu et al., 2019).** Moreover, in comparison to CNNs, GAN models often exhibit better results in fish recognition **(Zhao et al., 2018b).**

3.6 Challenges and Prospective Pathways

3.6.1 Technical Difficulties

Despite its numerous advantages, the use of deep learning in aquaculture encounters certain technological constraints. One of the primary obstacles is the necessity for wide, substantial, and high-quality datasets. Building strong AI models needs a lot of labeled data. But collecting and labeling data for fish-related information, like species classification, biomass estimation, and behavioral monitoring, is hard work that takes a lot of time **(Zhou et al., 2018b).** Also, being underwater can be hard because of things like poor vision, changing lighting, and cloudy water, all of which could make AI-based analysis of photos, videos, and sensor data less accurate **(Qin et al., 2016).** The primary concern is model generalization and transferability. Deep learning models work better in controlled experiments, but they have trouble with things that are hard to predict in the real world, like different types of aquatic habitats, a lot of different kinds of animals, and changes in the environment throughout the year **(Sun et al., 2018, Moniruzzaman et al., 2023).** The constraints of improved technology provide a challenge due to the large computing resources required for deep learning-based fish farming systems **(Saberioon et al., 2017; Mithun et al., 2024).**

3.6.2 Socioeconomic and Regulatory Challenges

The use of AI-driven deep learning technologies in aquaculture is not only a technological endeavor; it is also governed by economic and legal limitations. The substantial primary financial expenses associated with AI implementation provide a significant hurdle, particularly for small and medium-sized fish farms that have limited financial resources or technical knowledge to embrace AI-based solutions **(Kuddus et al., 2022; Ifty et al., 2023).** From a regulatory standpoint, data safety, security, and ethical considerations are growing concerns. The aggregation and use of aquaculture data raise inquiries regarding data ownership and security, along with possible hazards of proprietary information exploitation **(Zhuang et al., 2019).** Furthermore, the regulatory frameworks for AI-driven aquaculture are inadequately defined, resulting in ambiguities about compliance requirements and constraints in legal enforcement **(Pan & Yang, 2010).** Another critical reason is the reluctance of conventional fish farmers to embrace AI-driven technology, especially deep learning. Many aquaculture practitioners persist in utilizing traditional methods due to insufficient knowledge or a lack of understanding regarding the benefits of artificial intelligence. To promote the extensive use of AI-driven aquaculture solutions, training and workshop programs are essential to close this knowledge gap and enable effective implementation **(Banan et al., 2020; Begum et al., 2023b).**

3.7 Future Trends Advancements in AI and Policy Integration

Several steps will influence the development of deep learning in aquaculture, including the improvement of AI models for enhanced efficiency and accessibility. Advancements in federated learning and edge computing may provide real-time AI processing with reduced computer demands, making deep learning applications more viable for small-scale or minor aquaculture operations **(Moosavi-Dezfooli et al., 2016).** Another significant trend is the increased utilization of AI in conjunction with IoT and robots. To concurrently monitor environmental variables and fish behavior, intelligent aquaculture systems such as AI-driven sensors and automated feeding mechanisms will become more essential **(Hu et al., 2015, Begum et al., 2023a).** However, the integration of blockchain technology with AI can enhance transparency and traceability in the aquaculture supply chain, hence assuring food safety and regulatory compliance **(Fahad et al.,**

2022; Ashakin et al., 2024). By recognizing these issues and obstacles associated with harnessing future AI developments, deep learning technologies can significantly enhance the transition of fish farming into a more sustainable, efficient, and productive sector.

4. Conclusion

Deep learning (DL) has become a revolutionary tool in contemporary aquaculture, tackling significant difficulties through automated processes, machine learning, and real-time monitoring. This review focuses on how deep learning-based solutions, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), can greatly improve monitoring fish health, species classification, feeding decisions, biomass estimation, and water quality prediction. The use of artificial intelligence in aquaculture enhances resource efficiency, reduces environmental impact, and bolsters overall sustainability. There has been a lot of progress in using deep learning in aquaculture, but there are still some problems. For example, it takes a lot of processing power, it's hard to find high-quality datasets, and the models don't always work well in different aquatic ecosystems. Moreover, economic and legal obstacles, especially for small-scale aquaculture operations, impede broad adoption. To solve these issues, researchers, businesspeople, and policymakers need to work together across disciplines to create standardized AI frameworks, improve data-gathering methods, and make deep learning models easier to understand. Subsequent studies need to concentrate on the amalgamation of deep learning with Internet of Things (IoT) frameworks, edge computing, and blockchain technologies to improve scalability and data security. Federated learning methodologies may diminish computing expenses and facilitate collaborative AI training among several aquaculture enterprises. Ongoing breakthroughs in AI and machine learning position deep learning to transform the aquaculture business by enhancing efficiency, sustainability, and resilience in global fish farming techniques.

Funding

This work had no outside funding.

Author Contribution

The authors were involved in the creation of the study design, data analysis, fieldwork, and execution stages. Every writer gave their consent after seeing the final work.

Acknowledgments

We would like to thank the authors of the reviewed articles that was needed during the manuscript preparation.

A statement of conflicting interests

The authors declare that none of the work reported in this study could have been impacted by any known competing financial interests or personal relationships.

5. References

Acharya, D., Farazi, M., Rolland, V., Petersson, L., Rosebrock, U., Smith, D., Ford, J., Wang, D., Tuck, G. N., & Little, L. R. (2024). Towards automatic anomaly detection in fisheries using electronic monitoring and automatic identification system. Fisheries Research, 272, 106939. https://doi.org/10.1016/j.fishres.2024.106939

Alam, K., Chowdhury, M. Z. A., Jahan, N., Rahman, K., Chowdhury, R., Mia, M. T., & Mithun, M. H. (2023). Relationship between Brand Awareness and Customer Loyalty in Bangladesh: A Case Study of Fish Feed Company. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(3), 212-222.

Ahmad, S., Ahsan, J., Faisal, S., Ajmal, M., Mark, S., James, S., et al. (2016). Fish species classification in unconstrained underwater environments based on deep learning. Limnology and Oceanography: Methods, 14, 570-585. https://doi.org/10.1002/lom3.10125

Alcaraz, C., Gholami, Z., Esmaeili, H. R., & García-Berthou, E. (2015). Herbivory and seasonal changes in diet of a highly endemic cyprinodontid fish (Aphanius farsicus). Environmental Biology of Fishes, 98, 1541–1554. https://doi.org/10.1007/s10641-015-0381-y

Ashakin, M. R., Hossain, B., & Ifty, S. M. H. (2024). Enhancing digital signal processing: Obstacles and advancements in FPGA and ASIC hardware implementations. Pathfinder of Research, 2(2), 26–36.

Bahrampour, S., Ramakrishnan, N., Schott, L., & Shah, M. J. (2015). Comparative study of deep learning software frameworks. arXiv preprint arXiv:1511.06435.

Banan, A., Nasiri, A., & Taheri-Garavand, A. (2020). Deep learning-based appearance features extraction for automated carp species identification. Aquacultural Engineering, 89, 102053.

Begum, N. B. N., Chowdhury, M. E. C. M. E., Chowdhury, R. C. R., Begum, K. B. K., Selim, S. K. S. S. K., Hoque, J. H. J., & Sazzad, S. A. S. S. A. (2023a). Globalization and Textile Merchandising: How Global Supply Chains Influence Product Positioning and Market Research. Pathfinder of Research, 1(2), 13-13.

Begum, N. B. N., Mahmud, C. T. M. C. T., Chowdhury, M. E. C. M. E., Chowdhury, R. C. R., Begum, K. B. K., Selim, S. K. S. S. K., ... & Sazzad, S. A. S. S. A. (2023b). Innovative Visual Merchandising Strategies in the Digital Era: Enhancing Retail Consumer Engagement. Pathfinder of Research, 1(2).

Begum, N., Chowdhury, R., Khan, W., & Sazzad, S. A. (2022). Sustainable Merchandising: Integrating Eco-Friendly Practices in Retail Product Presentation. Pathfinder of Research, 3(1), 12-12.

Belthangady, C., & Royer, L. A. (2019). Applications, promises, and pitfalls of deep learning for fluorescence image reconstruction. Nature Methods, 16, 1215–1225. https://doi.org/10.1038/s41592-019-0458-z

Bronstein, M. M., Bruna, J., LeCun, Y., Szlam, A., & Vandergheynst, P. (2017). Geometric deep learning: Going beyond Euclidean data. IEEE Signal Processing Magazine, 34(4), 18–42. https://doi.org/10.1109/MSP.2017.2693418

Chen, L., Yang, X., Sun, C., & Wang, Y. (2019). Feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture. Information Processing in Agriculture, 7, 261–271.

Chowdhury, T. E. C. T. E., Chowdhury, R. C. R., Alam, S. S. A. S. S., & Sazzad, S. A. S. S. A. (2020). Empowering Change: The Impact of Microcredit on Social Business Development. *Pathfinder of Research*, *1*(1), 13-13.

Chowdhury, T. E. C. T. E., Chowdhury, R. C. R., Chaity, N. S. C. N. S., & Sazzad, S. A. S. S. A. (2021). From Shadows to Sunrise: The Impact of Solar Power Plants on Enhancing Bangladesh's Economy. *Pathfinder of Research*, *2*(1), 16-16.

Chowdhury, T. E. C. T. E., Chowdhury, R. C. R., Rahman, M. M. R. M. M., & Sunny, A. R. S. A. R. (2022). From Crisis to Opportunity: How Covid-19 Accelerated the Global Shift to Online Business. *Pathfinder of Research*, *3*(1), 18-18.

de Verdal, H., Komen, H., Quillet, E., Chatain, B., Allal, F., Benzie, J. A. H., et al. (2017). Improving feed efficiency in fish using selective breeding: A review. Reviews in Aquaculture, 10, 833-851.

Deng, H., Peng, L., Zhang, J., Tang, C., Fang, H., & Liu, H. (2019). An intelligent aerator algorithm inspired by deep learning. Mathematical Biosciences and Engineering, 16, 2990-3002.

Deng, L., & Yu, D. (2014). Deep learning: Methods and applications. Foundations and Trends in Signal Processing, 7(3-4), 197-387

Díaz-Gil, C., Smee, S. L., Cotgrove, L., Follana-Berna, G., Hinz, H., & Martí-Puig, P., et al. (2017). Using stereoscopic video cameras to evaluate seagrass meadows nursery function in the Mediterranean. Marine Biology, 164, 137.

Erickson, B. J., Korfiatis, P., Akkus, Z., Kline, T., & Philbrick, K. (2017). Toolkits and libraries for deep learning. Journal of Digital Imaging, 30, 400-405.

Fahad, M. A.H., Chowdhury, R., & Al-Shabbir, H. (2022). Evolution and future trends in web development: A comprehensive review. Pathfinder of Research, Special, 3(1). https://doi.org/10.69937/pf.por.3.1.35

Føre, M., Alver, M., Alfredsen, J. A., Marafioti, G., Senneset, G., Birkevold, J., et al. (2016). Modelling growth performance and feeding behaviour of Atlantic salmon (Salmo salar L.) in commercial-size aquaculture net pens: Model details and validation through full-scale experiments. Aquaculture, 464, 268–278

Franca Albuquerque, P. L., Garcia, V., da Silva Oliveira, A., Lewandowski, T., Detweiler, C., & Goncalves, A. B., et al. (2019). Automatic live fingerlings counting using computer vision. Computers and Electronics in Agriculture, 167, 105015.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Gouiaa, R., & Meunier, J. (2017). Learning cast shadow appearance for human posture recognition. Pattern Recognition Letters, 97, 54-60. https://doi.org/10.1016/j.patrec.2017.07.004

Granado, I., Hernando, L., Uriondo, Z., & Fernandes-Salvador, J. A. (2024). A fishing route optimization decision support system: The case of the tuna purse seiner. European Journal of Operational Research, 312(2), 718–732. https://doi.org/10.1016/j.ejor.2023.07.009

Hartill, B. W., Taylor, S. M., Keller, K., & Weltersbach, M. S. (2020). Digital camera monitoring of recreational fishing effort: Applications and challenges. Fish and Fisheries, 21, 204–215. https://doi.org/10.1111/faf.12421

Hassan, S. M. M., Sazzad, S. A., Selim, S. K., & Al Mozahid, A. (2024). Effect of Covid-19 Pandemic on Specific Crime in Dhaka, Bangladesh. *Pathfinder of Research*, *2*(2), 12-12.

Hinton, G. E., & Sejnowski, T. J. (1999). Unsupervised learning: Foundations of neural computation. MIT Press.

Hu, J., Li, D., Duan, Q., Han, Y., Chen, G., & Si, X. (2012). Fish species classification by color, texture and multi-class support vector machine using computer vision. Computers and Electronics in Agriculture, 88, 133-140. https://doi.org/10.1016/j.compag.2012.07.008

Hu, J., Wang, J., Zhang, X., & Fu, Z. (2015). Research status and development trends of information technologies in aquacultures. Transactions of the Chinese Society for Agricultural Machinery, 46, 251-263.

Hu, Z., Zhang, Y., Zhao, Y., Xie, M., Zhong, J., Tu, Z., et al. (2019). A water quality prediction method based on the deep LSTM network considering correlation in smart mariculture. Sensors, 19, 1420.

Ifty, S. M. H., Ashakin, M. R., Hossain, B., Afrin, S., Sattar, A., Chowdhury, R., Tusher, M. I., Bhowmik, P. K., Mia, M. T., Islam, T., & Sunny, A. R. (2023). IOT-based smart agriculture in Bangladesh: An overview. Applied Agriculture Sciences, 1(1), 1-10. https://doi.org/10.25163/agriculture.119563

Ifty, S. M. H., Hossain, B., Ashakin, M. R., Tusher, M. I., Shadhin, R. H., Hoque, J., Chowdhury, R., & Sunny, A. R. (2023). Adoption of IoT in agriculture: Systematic review. Applied Agriculture Sciences, 1(1), 1-10. https://doi.org/10.25163/agriculture.9676

Ifty, S. M. H., Irin, F., Shovon, M. S. S., Amjad, M. H. H., Bhowmik, P. K., Ahmed, R., Ashakin, M. R., Hossain, B., Mushfiq, Sattar, A., Chowdhury, R., & Sunny, A. R. (2024). Advancements, applications, and future directions of artificial intelligence in healthcare. Journal of Angiotherapy, 8(8), 1-18. https://doi.org/10.25163/angiotherapy.889843

Ketkar, N. (2017). Introduction to PyTorch. In Deep Learning with Python: A Hands-on Introduction (pp. 195-208).

Kuddus, M. A., Sunny, A. R., Sazzad, S. A., Hossain, M., Rahman, M., Mithun, M. H., ... & Raposo, A. (2022). Sense and Manner of WASH and Their Coalition with Disease and Nutritional Status of Under-five Children in Rural Bangladesh: A Cross-Sectional Study. *Frontiers in Public Health*, *10*, 890293.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436. https://doi.org/10.1038/nature14539

Levy, D., Belfer, Y., Osherov, E., Bigal, E., Scheinin, A. P., Nativ, H., et al. (2018). Automated analysis of marine video with limited data. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 1385-1393).

Li, D., Hao, Y., & Duan, Y. (2019). Nonintrusive methods for biomass estimation in aquaculture with emphasis on fish: A review. Reviews in Aquaculture. https://doi.org/10.1111/raq.12388

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., et al. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60-88. https://doi.org/10.1016/j.media.2017.07.005

Liu, S., Xu, L., Jiang, Y., Li, D., Chen, Y., & Li, Z. (2014). A hybrid WACPSO-LSSVR model for dissolved oxygen content prediction in crab culture. Engineering Applications of Artificial Intelligence, 29, 114-124.

Liu, Y., Zhang, Q., Song, L., & Chen, Y. (2019). Attention-based recurrent neural networks for accurate short-term and long-term dissolved oxygen prediction. Computers and Electronics in Agriculture, 165, 104964.

Liu, Z., Li, X., Fan, L., Lu, H., Liu, L., & Liu, Y. (2014). Measuring feeding activity of fish in RAS using computer vision. Aquacultural Engineering, 60, 20-27.

Lorenzen, K., Cowx, I. G., Entsua-Mensah, R., Lester, N. P., Koehn, J., & Randall, R., et al. (2016). Stock assessment in inland fisheries: A foundation for sustainable use and conservation. Review in Fish Biology and Fisheries, 26, 405-440.

Mahesh, S., Manickavasagan, A., Jayas, D. S., Paliwal, J., & White, N. D. G. (2008). Feasibility of near-infrared hyperspectral imaging to differentiate Canadian wheat classes. Biosystems Engineering, 101, 50-57. https://doi.org/10.1016/j.biosystemseng.2008.05.007

Marini, S., Fanelli, E., Sbragaglia, V., Azzurro, E., Del Rio Fernandez, J., & Aguzzi, J. (2018). Tracking fish abundance by underwater image recognition. Scientific Reports, 8, 13748.

Melnychuk, M. C., Peterson, E., Elliott, M., & Hilborn, R. (2017). Fisheries management impacts on target species status. Proceedings of the National Academy of Sciences, 114, 178–183.

Meng, L., Hirayama, T., & Oyanagi, S. (2018). Underwater-drone with panoramic camera for automatic fish recognition based on deep learning. IEEE Access, 6, 17880-17886.

Mhaskar, H. N., & Poggio, T. (2016). Deep vs. shallow networks: An approximation theory perspective. Analysis and Applications, 14, 829-848. https://doi.org/10.1142/S0219530516400037

Mithun, M. H., Shaikat, M. F. B., Sazzad, S. A., Billah, M., Al Salehin, S., Foysal, M., ... & Sunny, A. R. (2024). Microplastics in Aquatic Ecosystems: Sources, Impacts, and Challenges for

Biodiversity, Food Security, and Human Health-A Meta Analysis. Journal of Angiotherapy, 8(11), 1-12.

Moen, E., Handegard, N. O., Allken, V., Albert, O. T., Harbitz, A., & Malde, K. (2018). Automatic interpretation of otoliths using deep learning. PLoS One, 13, e0204713.

Moniruzzaman, Sazzad, S. A., Hoque, J., & Sunny, A. R. (2023). Influence of Globalization on Youth Perceptions on ChangingMuslim Rituals in Bangladesh. Pathfinder of Research, 1 (1), 11-22.

Moosavi-Dezfooli, S.-M., Fawzi, A., & Frossard, P. (2016). DeepFool: A simple and accurate method to fool deep neural networks. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 2574-2582). IEEE. https://doi.org/10.1109/CVPR.2016.282

Naddaf-Sh, M. M., Myler, H., & Zargarzadeh, H. (2018). Design and implementation of an assistive real-time red lionfish detection system for AUV/ROVs. Complexity, 2018, 1-10.

Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. Journal of Big Data, 2(1), 1–21. https://doi.org/10.1186/s40537-014-0007-7

Oosting, T., Star, B., Barrett, J. H., Wellenreuther, M., Ritchie, P. A., & Rawlence, N. J. (2019). Unlocking the potential of ancient fish DNA in the genomic era. Evolutionary Applications, 12, 1513-1522. https://doi.org/10.1111/eva.12809

Oquab, M., Bottou, L., Laptev, I., & Sivic, J. (2014). Learning and transferring mid-level image representations using convolutional neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1717-1724).

Pan, S. J., & Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22, 1345-1359.

Papadakis, V. M., Papadakis, I. E., Lamprianidou, F., Glaropoulos, A., & Kentouri, M. (2012). A computer-vision system and methodology for the analysis of fish behavior. Aquacultural Engineering, 46, 53-59.

Poggio, T., & Smale, S. (2003). The mathematics of learning: Dealing with data. In 2005 International Conference on Neural Networks and Brain (Vol. 50, pp. 537–544). IEEE. https://doi.org/10.1109/ICNNB.2005.1426420

Qiao, M., Wang, D., Tuck, G. N., Little, L. R., Punt, A. E., & Gerner, M. (2021). Deep learning methods applied to electronic monitoring data: Automated catch event detection for longline fishing. ICES Journal of Marine Science, 78(1), 25–35. https://doi.org/10.1093/icesjms/fsaa158

Qin, H., Li, X., Liang, J., Peng, Y., & Zhang, C. (2016). Deep Fish: Accurate underwater live fish recognition with a deep architecture. Neurocomputing, 187, 49-58. https://doi.org/10.1016/j.neucom.2015.10.122

Rahman, M. A., Ahmed, T., Rana, M. M., Hossain, B., Bhuiyan, M. R., & Alam, M. J. (2024, December 7-8). A comparative analysis of MCDM methods for selecting the optimal renewable energy source for Rajshahi, Bangladesh. 2024 International Conference on

Recent Progresses in Science, Engineering and Technology (ICRPSET), Faculty of Engineering, University of Rajshahi, Rajshahi, Bangladesh. IEEE.

Rahman, M. H., Islam, T., Amjad, M. H. H., Shovon, M. S. S., Chowdhury, M. E., Ashakin, M. R., Hossain, B., Bhowmik, P. K., Nurullah, M., & Sunny, A. R. (2024). Innovative IoT applications in healthcare: Enhancing patient care and overcoming challenges. Journal of Angiotherapy. https://doi.org/10.1007/s12026-024-09365-1

Rillahan, C., Chambers, M. D., Howell, W. H., & Watson, W. H. (2011). The behavior of cod (Gadus morhua) in an offshore aquaculture net pen. Aquaculture, 310, 361–368. https://doi.org/10.1016/j.aquaculture.2010.11.036

Romero-Ferrero, F., Bergomi, M. G., Hinz, R. C., Heras, F. J. H., & de Polavieja, G. G. (2019). idtracker.ai: Tracking all individuals in small or large collectives of unmarked animals. Nature Methods, 16, 179-182.

Roux, N. L., & Bengio, Y. (2008). Representational power of restricted Boltzmann machines and deep belief networks. Neural Computation, 20, 1631-1649.

Saberioon, M., & Cısar, P. (2018). Automated within-tank fish mass estimation using infrared reflection system. Computers and Electronics in Agriculture, 150, 484-492.

Saberioon, M., Gholizadeh, A., Cisar, P., Pautsina, A., & Urban, J. (2017). Application of machine vision systems in aquaculture with emphasis on fish: State-of-the-art and key issues. Reviews in Aquaculture, 9(4), 369–387. https://doi.org/10.1111/raq.12141

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. IBM Journal of Research and Development, 3(3), 210-229.

Saufi, S. R., Ahmad, Z. A. B., Leong, M. S., & Lim, M. H. (2019). Challenges and opportunities of deep learning models for machinery fault detection and diagnosis: A review. IEEE Access, 7, 122644-122662. https://doi.org/10.1109/ACCESS.2019.2937765

Sazzad, S. A. S. S. A., Ana, R. A. R. S. R., Shawon, R., Moniruzzaman, M., Hussain, M. H. M., & Zaman, F. Z. F. (2024). Climate Change and Socioeconomic Challenges of Fishing Communities in the Coastal District of Shariatpur in Bangladesh. *Pathfinder of Research*, *2*(1).

Sazzad, S. A., Billah, M., Sunny, A. R., Anowar, S., Pavel, J. H., Rakhi, M. S., ... & Al-Mamun, M. A. (2023). Sketching Livelihoods and Coping Strategies of Climate Vulnerable Fishers. *Egyptian Journal of Aquatic Biology & Fisheries*, *27*(4).

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117.

Siddiqui, S. A., Salman, A., Malik, M. I., Shafait, F., Mian, A., Shortis, M. R., et al. (2017). Automatic fish species classification in underwater videos: Exploiting pre-trained deep neural network models to compensate for limited labelled data. ICES Journal of Marine Science, 75, 374-389.

Sun, M., Hassan, S. G., & Li, D. (2016). Models for estimating feed intake in aquaculture: A review. Computers and Electronics in Agriculture, 127, 425-438.

Sun, R., Zhu, X., Wu, C., Huang, C., Shi, J., & Ma, L. (2019). Not all areas are equal: Transfer learning for semantic segmentation via hierarchical region selection. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 4355-4364).

Sun, X., Shi, J., Liu, L., Dong, J., Plant, C., Wang, X., et al. (2018). Transferring deep knowledge for object recognition in low-quality underwater videos. Neurocomputing, 275, 897–908. https://doi.org/10.1016/j.neucom.2017.09.048

Sunny, A. R., Islam, M. M., Nahiduzzaman, M., & Wahab, M. A. (2018). Coping with climate change impacts: The case of coastal fishing communities in upper Meghna hilsa sanctuary of Bangladesh. *Water Security in Asia: Opportunities and Challenges in the Context of Climate Change, Springer*, 1-9.

Sunny, A. R., Masum, K. M., Islam, N., Rahman, M., Rahman, A., Islam, J., ... & Prodhan, S. H. (2020). Analyzing livelihood sustainability of climate vulnerable fishers: Insight from Bangladesh. *Journal of Aquaculture Research and Development*, *11*(6), 593.

Sunny, A. R., Prodhan, S. H., Ashrafuzzaman, M., Sazzad, S. A., Aminur Rahman, S. M., Billah, M. M., ... & Alam, M. T. (2021a). Livelihoods and Vulnerabilities of Small-Scale Fishers to the Impacts of Climate Variability and Change: Insights from the Coastal Areas of Bangladesh. *Egyptian Journal of Aquatic Biology & Fisheries*, *25*(4).

Sunny, A. R., Prodhan, S. H., Ashrafuzzaman, M., Sazzad, S. A., Mithun, M. H., Haider, K. N., & Alam, M. T. (2021b). Understanding livelihood characteristics and vulnerabilities of small-scale fishers in coastal Bangladesh. *J Aqua Res Develop*, *12*, 635.

Ta, X., & Wei, Y. (2018). Research on a dissolved oxygen prediction method for recirculating aquaculture systems based on a convolution neural network. Computers and Electronics in Agriculture, 145, 302-310.

Terayama, K., Shin, K., Mizuno, K., & Tsuda, K. (2019). Integration of sonar and optical camera images using deep neural network for fish monitoring. Aquacultural Engineering, 86, 102000.

Thrall, J. H., Li, X., Li, Q., Cruz, C., Do, S., Dreyer, K., et al. (2018). Artificial intelligence and machine learning in radiology: Opportunities, challenges, pitfalls, and criteria for success. Journal of the American College of Radiology, 15, 504508.

Tripathi, M. K., & Maktedar, D. D. (2019). A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: A survey. Information Processing in Agriculture, 7(2), 183-203.

Villon, S., Mouillot, D., Chaumont, M., Darling, E. S., Subsol, G., Claverie, T., et al. (2018). A deep learning method for accurate and fast identification of coral reef fishes in underwater images. Ecological Informatics, 48, 238-244.

Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, 48, 144-156. https://doi.org/10.1016/j.jmsy.2018.06.012

Wang, S. H., Zhao, J. W., & Chen, Y. Q. (2017). Robust tracking of fish schools using CNN for head identification. Multimedia Tools and Applications, 76, 23679-23697.

White, D. J., Svellingen, C., & Strachan, N. J. C. (2006). Automated measurement of species and length of fish by computer vision. Fisheries Research, 80, 203–210. https://doi.org/10.1016/j.fishres.2006.04.009

Wu, T.-H., Huang, Y.-I., & Chen, J.-M. (2015). Development of an adaptive neural-based fuzzy inference system for feeding decision-making assessment in silver perch (Bidyanus bidyanus) culture. Aquacultural Engineering, 66, 41-51.

Xu, Z., & Cheng, X. E. (2017). Zebrafish tracking using convolutional neural networks. Scientific Reports, 7, 42815.

Yao, J., & Odobez, J. (2007). Multi-layer background subtraction based on color and texture. In 2007 IEEE Conference on Computer Vision and Pattern Recognition (pp. 1-8). IEEE. https://doi.org/10.1109/CVPR.2007.383025

Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In Lecture Notes in Computer Science (Vol. 8689, pp. 818-833). Springer. https://doi.org/10.1007/978-3-319-10590-1_53

Zhao, J., Bao, W., Zhang, F., Zhu, S., Liu, Y., Lu, H., et al. (2018). Modified motion influence map and recurrent neural network-based monitoring of the local unusual behaviors for fish school in intensive aquaculture. Aquaculture, 493, 165-175.

Zhao, J., Li, Y., Zhang, F., Zhu, S., Liu, Y., Lu, H., et al. (2018). Semi-supervised learning-based live fish identification in aquaculture using modified deep convolutional generative adversarial networks. Transactions of the ASABE, 61, 699-710.

Zheng, L., Yang, Y., & Tian, Q. (2017). SIFT meets CNN: A decade survey of instance retrieval. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40, 1224-1244. https://doi.org/10.1109/TPAMI.2017.2709749

Zhou, C., Sun, C., Lin, K., Xu, D., Guo, Q., Chen, L., et al. (2018). Handling water reflections for computer vision in aquaculture. Transactions of the ASABE, 61, 469-479. https://doi.org/10.13031/trans.12545

Zhou, C., Xu, D., & Lin, K., Sun, C., & Yang, X. (2018). Intelligent feeding control methods in aquaculture with an emphasis on fish: A review. Reviews in Aquaculture, 10, 975-993.

Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X., et al. (2019). Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision. Aquaculture, 507, 457–465.

Zhou, C., Yang, X., Zhang, B., Lin, K., Xu, D., Guo, Q., et al. (2017a). An adaptive image enhancement method for a recirculating aquaculture system. Scientific Reports, 7, 6243. https://doi.org/10.1038/s41598-017-06550-1

Zhou, C., Zhang, B., Lin, K., Xu, D., Chen, C., Yang, X., et al. (2017b). Near-infrared imaging to quantify the feeding behavior of fish in aquaculture. Computers and Electronics in Agriculture, 135, 233-241. https://doi.org/10.1016/j.compag.2017.01.024

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., & He, Q. (2019). A comprehensive survey on transfer learning. arXiv preprint arXiv:1911.02685.

Zion, B. (2012). The use of computer vision technologies in aquaculture: A review. Computers and Electronics in Agriculture, 88, 125-132. https://doi.org/10.1016/j.compag.2012.07.010