

DEEP LEARNING BASED FISH TANK MONITORING SYSTEM FOR CONTINUOUS FISH HEALTH MONITORING

A Project Report Phase – II

Submitted in partial fulfilment of the requirements for the award
of Bachelor of Engineering Degree in Electronics and
Communication Engineering

By

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Accredited with grade “A” by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Musani Praneeth (39130300)** and **BHARGAV BALGA (39130053)** who carried out the project entitled "**DEEP LEARNING BASED FISH TANK MONITORING SYSTEM FOR CONTINUOUS FISH HEALTH MONITORING**" under my supervision from November 2022 to April 2023.

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We, **MUSANI PRANEETH (39130300)** and **BHARGAV BALIGA (39130053)** here by declare that the Project Report **entitled " DEEP LEARNING BASED FISH TANK MONITORING SYSTEM FOR CONTINUOUS FISH HEALTH MONITORING "** done by us under the guidance of **Dr. M . SUBRAMONIAM, M.E., Ph. D.,** Associate Professor, Dept. of Electronics and Communication Engineering, Sathyabama institute of science and technology , Chennai, submitted partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

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Abstract

The rapid growth of deep learning (DL) technology is now being successfully used in a variety of sectors, including aquaculture. DL has a variety of effects on information and data processing in smarter fish farming, including new possibilities and challenges. Live fish identification, species categorization, behavioral analysis, food selection, size or biomass estimation, and water quality forecasting are among the uses of DL in aquaculture that are covered in this research. In addition, the efficacy of the DL approach used in smart fish farming is evaluated along with the data, algorithms, and performance. The review's conclusions show that DL's ability to automatically extract features is its most significant addition. However, there are still issues. For instance, deep learning training needs a sizeable amount of labelled data, which is still a relatively new development in AI. Stage and has turned into a bottleneck that prevents further DL applications in aquaculture because it needs a significant quantity of labelled data for training. However, DL continues to provide innovations for handling complicated data in aquaculture. In a nutshell, our goal is to give academics and practitioners a better grasp of the state-of-the-art in DL in aquaculture, which can be an excellent foundation for implementing smart fish farming applications.

Keywords: Deep learning; Smart fish farming; Advanced analytics; Aquaculture;

CONTENTS

CHAPTER NO	TITLE		PAGE No.
	ABSTRACT		v
	LIST OF FIGURES		viii
1	INTRODUCTION		1
2	LITERATURE SURVEY		4
	2.1	Literature Survey	4
	2.2	Objective	9
3	PROPOSED METHODOLOGY		11
	3.1	Terms and definition of Deep Learning	11
	3.2	Learning tasks and modules	12
	3.3	Applications of Deep Learning in smart fish farming	14
	3.4	Live fish identification	15
	3.5	Species classification	16
	3.6	Behavioral analysis	18
	3.7	Size or Bio mass estimation	19
	3.8	Feeding Decision making	21
	3.9	Water quality prediction	23
	3.10	Technical details with data	24
	3.11	Models framework	25
	3.12	Tensor flow	27
4	MERITS AND DEMERITS		28

	4.1	Advantages of Deep Learning	28
	4.2	Disadvantages of Deep Learning	29
5	RESULTS AND DISCUSSION		31
	5.1	Training Module	31
	5.2	Fish Detection	32
	5.3	Graphical Representation	35
	5.4	Final Analysis	37
6	CONCLUSION		38
	7.1	Future technical trends of deep learning in aquaculture	38
	7.2	Challenges	40
	7.3	Notable IEEE Standard Committee	41
	7.4	References	44
7	RESEARCH PAPER		46

LIST OF FIGURES AND TABLES

FIGURE NO	NAME	PAGE No.
1.1	The role of Deep Learning and big data in smart farming	1
1.2	Training block diagram	3
2.1	Cycle representation of PFF	8
2.2	Illustration of how four systems based on different monitoring principles could be deployed in a commercial cage to observe the fish	9
3.1	An example of DL model	11
3.2	Comparison of DL and Machine Learning	12
3.3	Deep Learning enabled advanced analytics for smart fish farming	13
3.4	Number of papers addressing different application scenarios	14
3.5	An illustration of the fish classification process	17
3.6	Feeding decisions	22
3.7	Water quality prediction	24
3.8	Typical example of transfer learning	26
5.1	Output 1	33
5.2	Output 2	33
5.3	Output 3	34
5.4	Feeding rate	35
5.5	Weight analysis	35
5.6	Diagram to calculate fish weight	36
5.7	Fish size	36
5.8	Status of fishes (table)	37

Chapter 1

Introduction

In 2016, the global fishery output reached a record high of 171 million tons. Of this output, 88% is consumed directly by human beings and is essential for achieving the Food and Agriculture Organization of the United Nations (FAO)'s goal of building a world free from hunger and malnutrition (FAO, 2018). However, as the population continues to grow, the pressure on the world's fisheries will continue to increase.

Smart fish farming refers to a new scientific field whose objective is to optimize the efficient use of resources and promote sustainable development in aquaculture through deeply integrating the Internet of Things (IoT), big data, cloud computing, artificial intelligence and other modern information technologies. Furthermore, the real-time data collection, quantitative decision-making, intelligent control, precise investment and personalized service, have been achieved, finally forming a new fishery production mode.

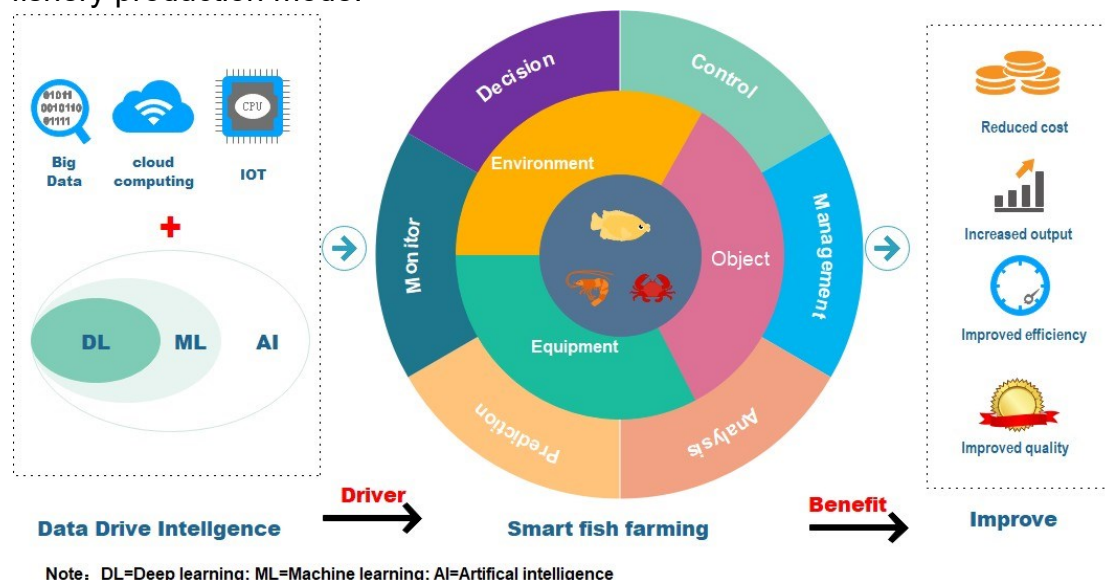


Figure 1.1 The role of Deep Learning and Big Data in smart fish farming

In smart fish farming, data and information are the core elements. The aggregation and advanced analytics of all or part of the data will lead to the ability to make scientifically based decisions. However, the massive amount of data in smart fish farming imposes a variety of challenges, such as multiple sources, multiple formats

and complex data. Multiple sources include information regarding the equipment, the fish, the environment, the breeding process and people. The multiple formats include text, image and audio. The data complexities stem from different cultured species, modes and stages. Addressing the above high-dimensional, nonlinear and massive data is an extremely challenging task.

More attention is being paid to data and intelligence in current fish farming than ever before. As shown in Figure 1.1, data-driven intelligence methods, including artificial intelligence and big data, have begun to transform these data into operable information for smart fish farming. Artificial intelligence, especially machine learning and computer vision applications, is the next frontier technology of fishery data systems. Traditional machine learning methods, such as the support vector machine, artificial neural networks (ANN), decision trees, and principal component analysis, have achieved satisfactory performances in a variety of applications. However, the conventional machine learning algorithms rely heavily on features manually designed by human engineers, and it is still difficult to determine which features are most suitable for a given task.

As a breakthrough in artificial intelligence (AI), deep learning (DL) has overcome previous limitations. DL methods have demonstrated outstanding performances in many fields, such as agriculture, natural language processing, medicine, meteorology, bioinformatics, and security monitoring. DL techniques can be used to solve the problems of limited intelligence and poor performance in the analysis of massive, multisource and heterogeneous big data in aquaculture. By combining the IoT, cloud computing and other technologies, it is possible to achieve intelligent data processing and analysis, intelligent optimization and decision-making control functions in smart fish farming.

It is an important task to reliably detect and track multiple moving objects for video surveillance and monitoring. However, when occlusion occurs in nonlinear motion scenarios, many existing methods often fail to continuously track multiple moving objects of interest. In this project we propose an effective approach for detection and tracking of multiple moving objects with occlusion. Moving targets are initially detected using a simple yet efficient block matching technique, providing rough location information for multiple object tracking.

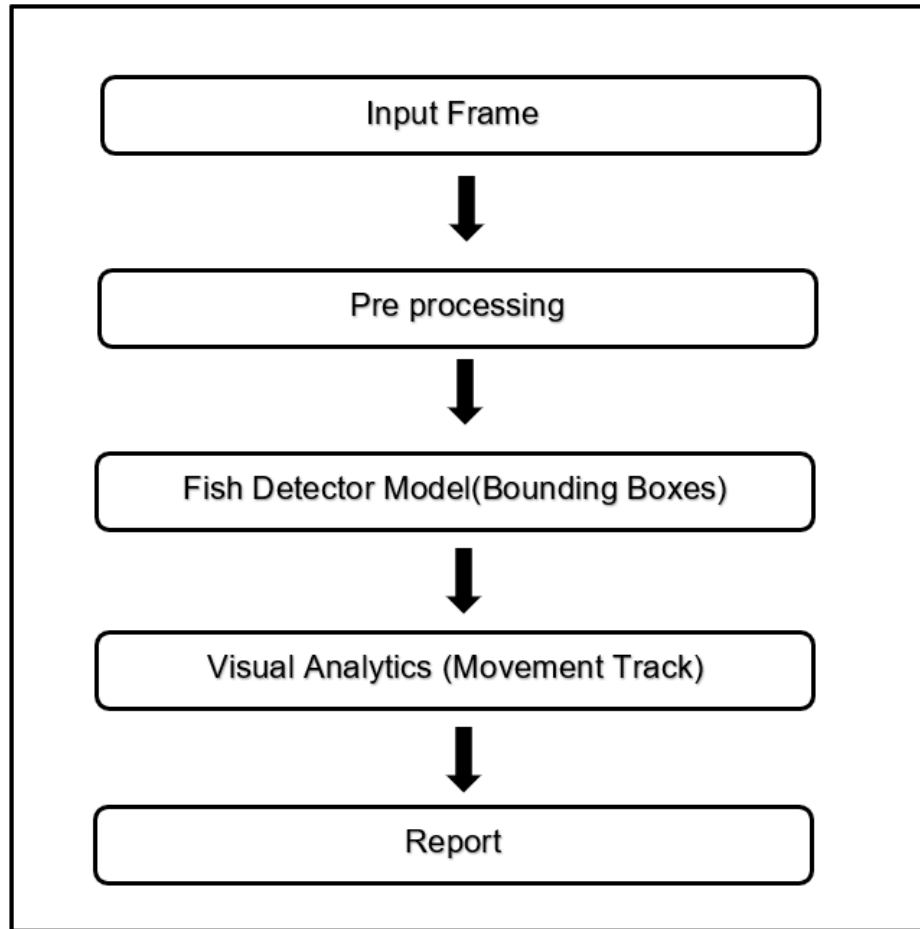


Figure 1.2. Steps Involved in Training Process

First, the various DL applications related to aquaculture are outlined to highlight the latest advances in relevant areas, and the technical details are briefly introduced. Then, the challenges and future trends of DL in smart fish farming are discussed. This report is organized as follows: Section 2 describes basic background knowledge such as DL terminology, definitions, and the most popular learning models and algorithms. Section 3 provides technical details and Section 4 discusses the advantages, disadvantages. Section 5 describes the results and discussion. Section 6 discusses the future trends, challenges of DL in smart fish farming.

Chapter 2

Literature Survey

2.1 Literature Survey

The most important future objective is the extension of the RMS index-based design strategy to the third-order (and higher order) Kalman filters that are widely used for real applications. In third-order tracking, an acceleration is added to the state vector, becoming one of the input parameters of the Kalman filter. Performance analysis and the establishment of a design Figure 4. Simulation results. Kalman Filter for Moving Object Tracking: Performance Analysis and Filter Design <http://dx.doi.org/10.5772/intechopen.71731> 247 strategy for such systems (i.e., position/acceleration and position/velocity/acceleration measured Kalman filters) are important considerations for advanced sensor fusion systems under development. Moreover, considerations of other dynamic models (e.g., the constant turn model) should also be probed for use in many applications including pedestrian tracking.

Technological advances over the last decades have enabled the development of several PLF methods and application areas, including the use of modern sensor technologies to monitor animal variables (e.g. Darr and Epperson, 2009, Tebot et al., 2009), using methods from information technology and modelling to synthesise and combine different types of data (e.g. Milner-Gulland et al., 2006, Terrasson et al., 2016), and the application of control theory to increase the level of autonomy (see Johnson et al., 2011 on different autonomy levels) of the production process (Frost et al., 2003). While most of these applications have arisen from research activities, the long-term goal of PLF is to provide industrial methods and tools that contribute to improving animal health and welfare while increasing productivity, yield and environmental sustainability. This is generally achieved through the combination of hardware and intelligent software (Berckmans, 2014). Examples of successful PLF applications in the livestock production industry include the automated monitoring of pig health through cough analysis with microphones (Berckmans, Hemeryck, Berckmans, Vranken, & van Waterschoot, 2015), the utilisation of automated milking robots on cows (John et al., 2016), and the use

of computer vision methods to automatically monitor real time positions of animals (Sloth & Frederiksen, 2015)

Here the Author has developed the Precision Fish Farming (PFF) concept that is based on Precision Livestock Farming(PLF) and hence accommodates the features therein, while also addressing the additional challenges of farming animals in water. In this article the PFF framework is presented by first defining the boundary conditions and possibilities of precision farming in the aquatic environment, then defining the PFF concept in brief terms, and then going through the status of PFF today, within the framework of research and industry. Following this, The potential industrial impacts of PFF is exemplified by four specific case studies, before it is concluded and recommend for future research directions, It is deemed important for the continued development of the PFF concept. Her Author has primarily used examples related to Atlantic salmon farming, because this is a segment of industrial fish farming that has a high technology level, is under rapid development, and hence will be very receptive with respect to PFF-methods. However, the Author believed that the applications of PFF will be transferrable to other aquatic farmed species.

Over the millennia that terrestrial livestock farming has been a part of human culture, the interaction between man and animal has produced a vast body of veterinary, ethological and physiological knowledge on farm animals. Through such knowledge, humans have been able to identify how observable traits and bio-responses exhibited by animals may be linked with management outcomes such as growth (e.g. Tedeschi, Fox, & Guiray, 2004), health/survival (e.g. Berckmans et al., 2015) and milk production (e.g. John et al., 2016). This process is analogous to the *system identification* methods used in control engineering to determine relationships between system inputs and system outputs when lacking a complete mechanistic description of key sub-systems (Åström & Eykhoff, 1971). Establishing an understanding of such relationships is a prerequisite for being able to derive the sequence from an observed bio-response, through Animal and Feature variables, to Target variables that lies at the core of the PLF concept. Moreover, a thorough understanding of the system dynamics is also key in identifying possible Gold Standards to validate such methods.

Direct man and animal interaction is more difficult in fish farming than in its terrestrial counterpart, and the population sizes in fish aquaculture make interactions with specific individuals very difficult. Furthermore, intensive cage-based fish farming has a comparatively shorter industrial history (decades) than terrestrial livestock production (millennia). As a result, knowledge about the bioprocesses occurring in industrial fish farming is very limited compared with terrestrial farming; this makes proper system identification a more challenging task. Moreover, it means that the identification of both relationships between bio-responses and target variables and proper Gold Standards will often be more difficult and likely to be based on a weaker foundation in a fish farming situation.

In addition to influencing the knowledge foundation for deriving PFF methods, the aforementioned factors also complicate the operational aspects of implementing such methods. For instance, it is generally challenging to continuously monitor animals and achieve sufficient information for PFF applications in the aquatic environment. While such information may be obtained using direct observation or low-end technological equipment on land, more advanced technical solutions are required to achieve a similar knowledge basis in fish farms, where one needs to cope with the unforgiving conditions of the subsurface environment at increasingly exposed sites, and the large number of animals at each farm. Moreover, the establishment of Gold Standards may be complicated by the difficulties in directly interacting with individuals. Many Gold Standards used in terrestrial farming require veterinarians or farmers to directly observe and/or interact with the animals, an ability that may be rendered near impossible in commercial fish farms. In spite of all these challenges, the technologies used today by farmers to observe the fish represent good foundations for developing future PFF applications, and often entail already established technical infrastructures for communication and power supply. Furthermore, since farmers are already accustomed to employing technical solutions in their everyday work tasks, the introduction of new technology based upon PFF methods will not represent a completely new concept.

As fish farms increase in size and complexity, the size and designs of fish cages evolve, and new location types are taken into use (e.g. Bjelland et al., 2015,

pp. 1–10), more sophisticated technological solutions will be required to provide sufficient knowledge and information to monitor and/or control the biological production process. Furthermore, a side effect of the increases in scale occurring within the industry is that risks associated with day-to-day operations are also increasing (Kalogerakis et al., 2015). Larger structures sustain larger loads, making handling and manipulation of structural components such as the net or sinker tubes more precarious activities (Lader, Dempster, Fredheim, & Jensen, 2008). In the event of component breakdown during such operations, the forces released in modern fish farms are more likely to cause serious injuries than was the case decades ago. Moreover, with larger populations in each cage, potential negative consequences of suboptimal animal handling such as escapes (Jensen, Dempster, Thorstad, Uglem, & Fredheim, 2009) and impaired welfare (Pettersen et al., 2014) will also increase. Using technology to automate or otherwise increase the security of such operations could thus lead to vast improvements in risk mitigation around commercial fish farms, which might be one of the most important outcomes of using the PFF approach.

In addition, the Norwegian government presently has an arrangement where salmon production companies are awarded new fish production permits (so-called development permits) if they develop new concepts for sustainable production of salmon. How the fish will respond to and grow in new and untested production concepts is largely unknown. Furthermore, many of these concepts include larger fish populations being kept in each production unit (i.e. cages or tanks). Although such concepts also include increasing the volumes of the production units accordingly to achieve comparable stocking densities to those commonly used today, the surface area of the cage facing the upstream current does not scale with the same factor. For example, if the population and correspondingly the production unit volume is upscaled by a factor of five, the upstream facing cage area will scale by a factor of less than three. As a consequence, the water exchange rate does not scale properly with the population (Lader et al., 2008). This may lead to hypoxic conditions in the cage as the oxygen consumption of the fish may then exceed the oxygen replenishment through incoming water. Poor dissolved oxygen conditions reduce the appetite and subsequent growth rates of. This development emphasises the need for better methods to manage and monitor the populations in commercial

fish production systems. Thus the Author argues that the potential industrial impact of PFF may equal or even exceed that of PLF.

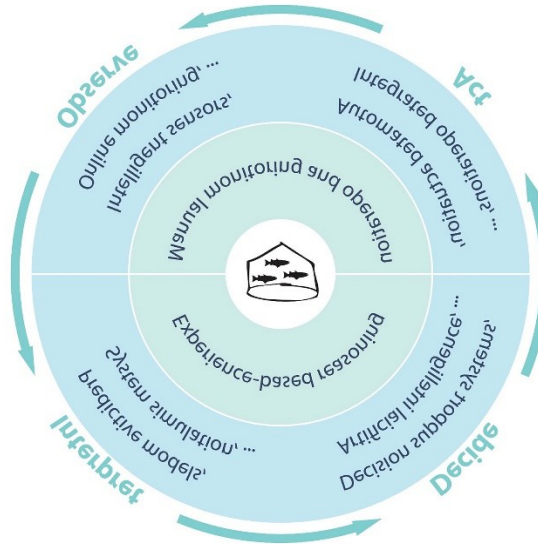


Figure 2.1 Cyclical Representation of PFF

Today, most tasks pertaining to the different phases are conducted manually (i.e. close to the centre in Fig. 2.1). First, the farmer observes the fish via direct visual observation or with data acquisition tools such as cameras, the outcome of which is qualitative or quantitative information on the bio-responses of the fish. The farmer then uses primarily subjective experience to interpret this information, yielding a perception of the current state and condition of the fish. These interpretations are then used as a foundation for making decisions concerning farming operations and management, which are then put into action by manually induced actions on the cage. Such decisions may be made based on the estimated present states or expected future states of the system, representing manual versions of the feedback and feed-forward principles in control engineering respectively.

Methods and tools for fish farming that apply technological solutions and/or automation principles to one, several or all the different phases of farming operations may be considered PFF approaches. The ultimate result of applying PFF to a particular operation will therefore be that the elements in that operation belonging to the different phases of fish farming operations are shifted from an experience-based to a knowledge-based regime

Although the PFF concept has not previously been defined, many technological research efforts and equipment innovations for the fish aquaculture industry can be considered tools or components for developing PFF methods, and in a few cases are already PFF methods in their own right. Here, the Author provide an overview of the present status in this area, covering both industrial applications and research activities. Most relevant methods or concepts included here address a single phase in fish farming operations (Fig. 2.1), hence a status will be given separately for each phase

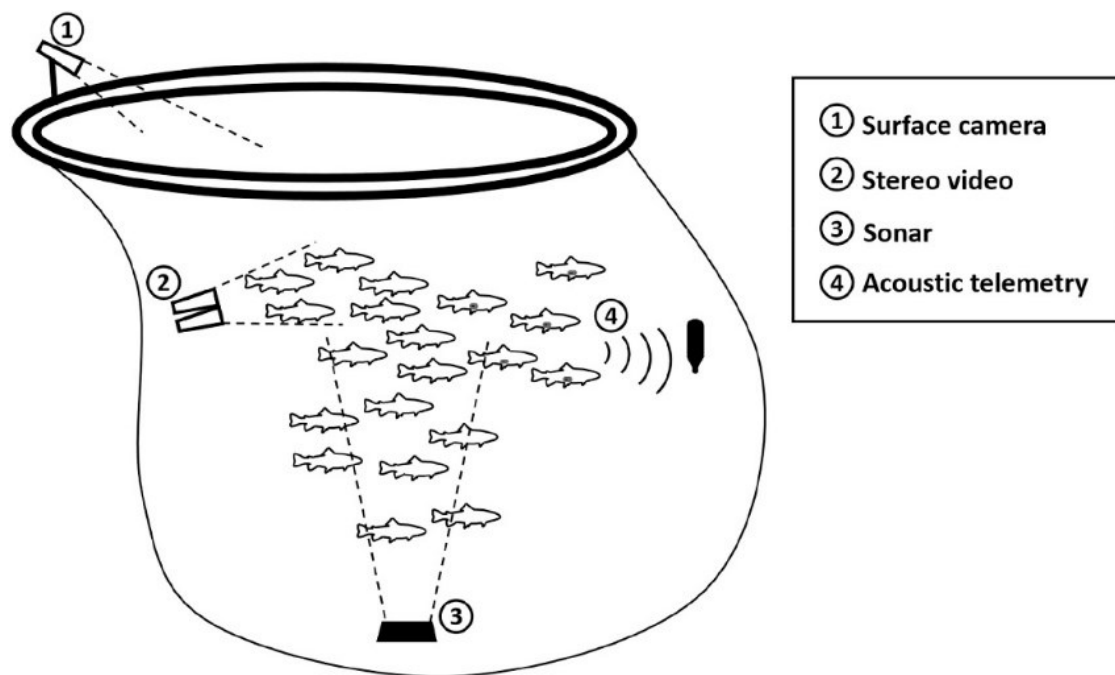


Figure 2.2 *Illustration of how four systems based on different monitoring principles could be deployed in a commercial cage to observe the fish*

2.2 Objective

The rapid emergence of deep learning (DL) technology has resulted in its successful use in various fields, including aquaculture. DL creates both new opportunities and a series of challenges for information and data processing in smart fish farming. This project focuses on applications of DL in Fish detection, including live fish identification, species colour, fish path tracking, estimating size of fishes. The technical details of DL methods applied to smart fish farming are included, such as data, algorithms, and performance. The review results show that the most significant contribution of DL is its ability to automatically extract features. However,

challenges still exist; DL is still in a weak artificial intelligence stage and requires large amounts of labeled data for training, which has become a bottleneck that restricts further DL applications in aquaculture. Nevertheless, DL still offers breakthroughs for addressing complex data in aquaculture. In brief, our purpose is to provide researchers and practitioners with a better understanding of the current state of the art of DL in aquaculture, which can provide strong support for implementing smart fish farming applications.

Chapter 3

Proposed Methodology

3.1 Terms and definitions of deep learning

Machine learning (ML), which emerged together with big data and high-performance computing, has created new opportunities to unravel, quantify, and understand data-intensive processes. ML is defined as a scientific field that seeks to give machines the ability to learn without being strictly programmed. Deep learning is a branch of machine learning and is a type of representation learning algorithm based on an artificial neural network. Specifically, DL is a type of machine learning that can be used for many (but not all) AI tasks.

DL enables computers to build complex concepts from simpler concepts, thus solving the core problem of representation learning. It is difficult for computers to directly understand the meaning contained in raw sensory input data, such as an image represented as a set of pixels. The functions that map a set of pixels to an object are highly complex. It seems impossible to learn or evaluate such a mapping through direct programming. To solve this problem, DL decomposes this complex mapping into a nested series of simpler mappings. For example, an image is input in the visible layer, followed by a series of hidden layers that extract increasingly abstract features from the image. Given a pixel, by comparing the brightness of adjacent pixels, the first layer could easily identify whether this pixel represents an edge. Then, the second hidden layer searches for sets of edges that can be recognized as angles and extended contours. The third hidden layer can then find a specific set of contours and corners that represent an entire portion of a particular object. Finally, the various objects existing in the image can be identified.

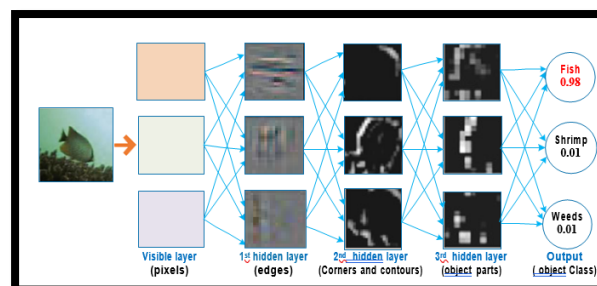


Figure 3.1. An example of a DL model

3.2 Learning tasks and models

In general, a DL method involves a learning process whose purpose is to gain "experience" from samples to support task execution. DL methods can be divided into two categories: supervised learning and unsupervised learning (Goodfellow, 2016). In supervised learning, data are presented as labeled samples consisting of inputs and corresponding outputs. The goal is to construct mapping rules from the input to output. The convolutional neural network (CNN) and the recurrent neural network (RNN) are two typical popular model architectures. Inspired by the human visual nervous system, CNNs excel at image processing, while an RNN can process sequential data effectively. In unsupervised learning, the data are not labeled; instead the model seeks previously undetected patterns in a dataset with no pre-existing labels and with minimal human supervision (Geoffrey E Hinton, 1999). The generative adversarial network (GAN) is one of the most promising unsupervised learning approaches. A GAN can produce good output through mutual game learning of two (at least) modules in the framework: a generative model and a discriminative model. Many modified or improved models have been derived based on these original DL models, such as the region convolutional neural network (R-CNN) and long short-term memory (LSTM) models.

Figure 3 shows a comparison of traditional machine learning and DL. In DL, feature learning and model construction are integrated into a single model via end-to-end optimization. In traditional machine learning, feature extraction and model construction are performed separately, and each module is constructed in a step-by-step manner.

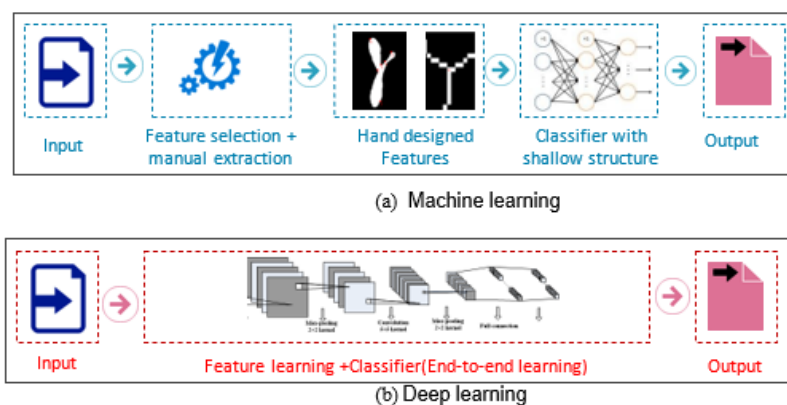


Figure 3.2 Comparison of Deep Learning and Machine Learning

Compared with the shallow structure of traditional machine learning, the deep hierarchical structure used in DL makes it easier to model nonlinear relationships through combinations of functions. The advantages of DL are especially obvious when the amount of data to be processed is large. More specifically, the hierarchical learning and extraction of different levels of complex data abstractions in DL provides a certain degree of simplification for big data analytics tasks, especially when analyzing massive volumes of data, performing data tagging, information retrieval, or conducting discriminative tasks such as classification and prediction. Hierarchical architecture learning systems have achieved superior performances in several engineering applications.

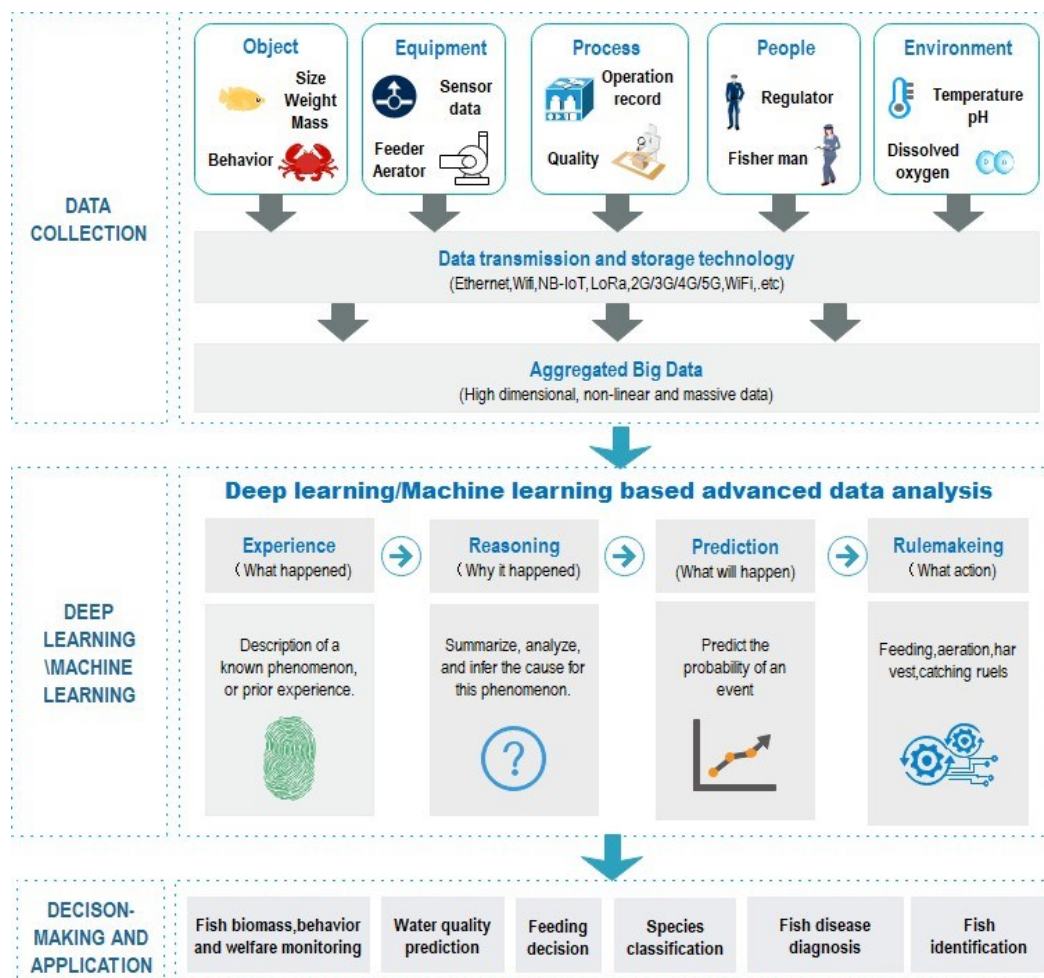


Figure 3.3 Deep learning enabled advanced analytics for smart fish farming

The overall structure, process and principles of applying deep learning to fishery management is depicted in Figure 3.3. After the data are collected and transmitted, deep learning performs inductive analysis, learns the experience or knowledge from the samples, and finally formulates rules to guide management decisions.

However, when applying deep learning, the most serious issue is that of hallucination. Another failure mode of neural networks is overlearning or overfitting. In addition, neural networks can be tricked into producing completely different outputs after imperceptible perturbations are applied to their inputs.

3.3 Applications of deep learning in smart fish farming

The relevant applications can be divided into 6 categories: live fish identification, species classification, behavioral analysis, feeding decisions, size or biomass estimation, and water quality prediction. Figure 3.4 shows the number of papers related to each application. The most popular fields are live fish identification and species classification. Notably, all these papers were published in 2016 or later, including 3 in 2016, 3 in 2017, 12 in 2018, 15 in 2019, and 8 in 2020, indicating that DL has developed rapidly since 2016. In addition to water quality prediction and sound recognition, most papers involve image processing. Moreover, while most of the papers are focused on fish, a few works consider lobsters or other aquatic animals.

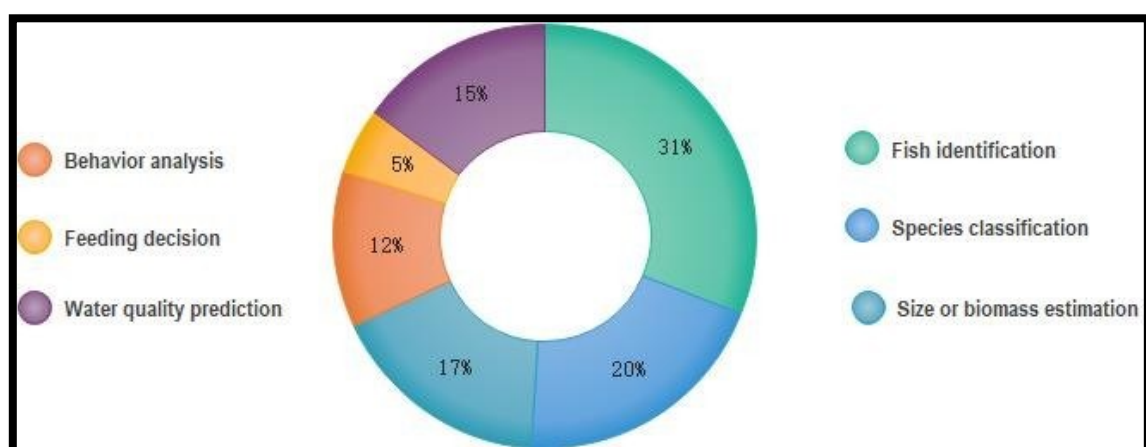


Figure 3.4 Representing the number of papers addressing different application scenario

3.4 Live fish identification

Accurate and automatic live fish identification can provide data support for subsequent production management; thus, fish identification is an important factor in the development of intelligent breeding management equipment or systems. Machine vision has the advantages of enabling long-term, nondestructive, noncontact observation at low cost. However, the scenes encountered in aquaculture present numerous challenges for image and video analysis. First, the image quality is easily affected by light, noise, and water turbidity, resulting in relatively low resolution and contrast.

Second, because fish swim freely and are uncontrolled targets, their behavior may cause distortions, deformations, occlusion, overlapping and other disadvantageous phenomena. Most current image analysis methods are adversely affected by these difficulties.

While many studies have been conducted to investigate the above issues, most emphasized the extraction of conventional low-level features, which usually involve small details in an image such as feature points, colors, textures, contours, and shapes of interest. In practical applications, the effects of methods based on such features is often unsatisfactory. DL involves multilevel data representations, from low to high levels, in which high-level features are built on the low-level features and carry rich semantic information that can be used to recognize and detect targets or objects in the image. Generally, both types of features are used in convolutional neural networks: the first few layers learn the low-level features, and the last few layers learn the high-level features. This approach has the potential to solve the problems listed above.

To meet the needs of some embedded systems, such as underwater drones, real-time performance by DL models are the key to their practicability. It has been experimentally shown that using an unmanned aerial vehicle (UAV)-type system to observe objects on the sea surface, a CNN can effectively recognize a swarm of jellyfish, and can achieve reasonable performance levels (80% accuracy) for real-world applications. After DL model training is complete, such models can show excellent speed for live fish identification purposes. For example,

one model required only 6 s to identify 115 images; the average time to detect lionfish in each frame was only 0.097s. Therefore, under the premise of reasonable accuracy, a DL model's recognition speed can satisfy real-time requirements. Hence, DL can be effectively applied to identify fish while meeting the rapid response and real-time requirements of embedded systems.

For identifying live fish, DL is mainly used to solve the problem of whether a given object is a fish. In this era, where large amounts of visual data can be collected easily, DL can be a practical machine vision solution. Therefore, it is worth studying the performance levels that can be achieved by combining DL and machine vision to explore fast and accurate methods. The main disadvantage of DL is that it requires a large amount of labeled training data, and obtaining and annotating sufficiently large numbers of images is time-consuming and laborious. Moreover, the recognition effect depends on the quality of the training samples and annotation.

3.5 Species classification

Fish are diverse, with more than 33,000 species. In aquaculture, species classification is helpful for yield prediction, production management, and ecosystem monitoring. Fish species can usually be distinguished by visual features such as size, shape, and color. However, due to changes in light intensity and fish motion as well as similarities in the shapes and patterns among different species, accurate fish species classification is challenging.

DL models can learn unique visual characteristics of species that are not sensitive to environmental changes and variations. Taking a given underwater video as an example (Figure 3.5), an object detection module first generates a series of patch proposals for each frame F . Each patch is then used as an input to the classifier, and a label distribution vector is obtained. The tags with the highest probability are regarded as the tags of these patches.

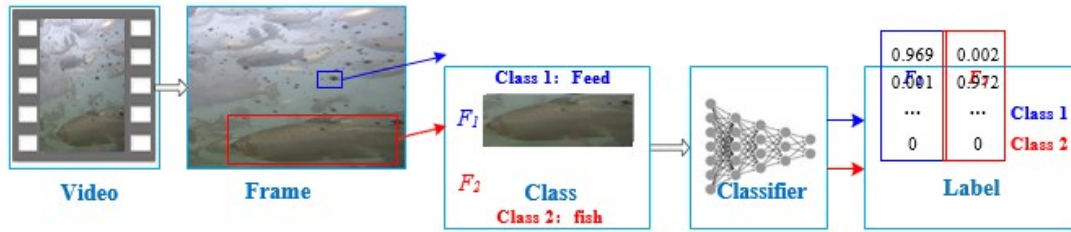


Figure 3.5 Illustration of the fish classification process

A DL model can better distinguish differences in characteristics, categories, and the environment, which can be used to extract the features of target fish from an image collected in an unconstrained underwater environment. Fish species can be classified to identify several basic morphological features. Most of the DL models show better results compared with the traditional approaches, reaching classification accuracies above 90% on the LifeCLEF 14 and LifeCLEF 15 benchmark fish datasets. To avoid the need for large amounts of annotated data, general deep structures must be fine-tuned to improve the effectiveness with which they can identify the pertinent information in the feature space of interest. Accordingly, various DL models for identifying fish species have been developed using a pretrained approach called transfer learning. By fine-tuning pretrained models to perform fish classification using small-scale datasets, these approaches enable the network to learn the features of a target dataset accurately and comprehensively, and achieved sufficiently high accuracy to serve as economical and effective alternatives to manual classification.

In addition to visual characteristics, different species of grouper produce different sound frequencies that can be used to distinguish these species. For example, CNN and LSTM models were used to classify sounds produced by four species of grouper; their resulting classification accuracy was significantly better than the previous weighted Mel-frequency cepstral coefficients (WMFCCs) method. Nevertheless, due to the influence of various interferences and the small sets of available samples, the accuracy of same-species classification still has considerable room to improve. Most current fish classification methods are designed to distinguish fish with significant differences in body size or shape; thus, the classification of similar fish and fish of the same species is still challenging.

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3.6 Behavioral analysis

Fish are sensitive to environmental changes, and they exhibit a series of responses to changes in environmental factors through behavioral changes. In addition, behavior serves as an effective reference indicator for fish welfare and harvesting. Relevant behavior monitoring, especially for unusual behaviors, can provide a nondestructive understanding and an early warning of fish status. Real-time monitoring of fish behavior is essential in understanding their status and to facilitate capturing and feeding decisions.

Fish display behavior through a series of actions that have a certain continuity and time correlations. Methods of identifying an action from a single image will lose relevance for images acquired before and after the action. Therefore, it is desirable to use time-series information related to the prior and subsequent frames in a video to capture action relevance. DL methods have shown strong ability to recognize visual patterns. Table 3 shows the details of the behavioral analysis using DL. In particular, due to their powerful modeling capabilities for sequential data, RNNs have the potential to address the above problem effectively. Zhao *et al.* proposed a novel method based on a modified motion influence map.

Tracking individuals in a fish school is a challenging task that involves complex nonrigid deformations, similar appearances, and frequent occlusions. Fish heads have relatively fixed shapes and colors that can be used to track individual fish. Thus, data associations can be achieved across frames, and as a result, behavior trajectory tracking can be implemented without being affected by frequent occlusions. In addition, data enhancement and iterative training methods can be used to optimize the accuracy of classification tasks for identifying behaviors that cannot be distinguished by the human eye. Finally, ID Tracker and further developments in identification algorithms for unmarked animals have been successful for 2~15 individuals in small groups. An improved algorithm, called Idtracker.ai has also been proposed. Using two different CNNs, Idtracker.ai can track all the individuals in both small and large groups (up to 100 individuals) with a recognition accuracy that typically exceeds 99.9%.

When using deep learning to classify fish behavior, crossing, overlapping and blocking caused by free-swimming fish and low-quality environmental images form the main challenges to behavior analysis; thus, these problems need to be solved in the future.

3.7 Estimating size and biomass

It is essential to continuously observe fish parameters such as abundance, quantity, size, and weight when managing a fish farm. Quantitative estimation of fish biomass forms the basis of scientific fishery management and conservation strategies for sustainable fish production. However, it is difficult to estimate fish biomass without human intervention because fish are sensitive and move freely within an environment where visibility, lighting and stability are typically uncontrollable.

Recent applications of DL to fishery science offer promising opportunities for

massive sampling in smart fish farming. Machine vision combined with DL can enable more accurate estimation of fish morphological characteristics such as length, width, weight, and area. Most reported applications have been either semi supervised or supervised. For example, the Mask R-CNN architecture was used to estimate the size of saithe (*Pollachius virens*), blue whiting, redfish (*Sebastes spp.*), Atlantic mackerel, velvet belly lantern shark, Norway pout, Atlantic herring and European hake.

Another method for indirectly estimating fish size is to first detect the head and tail of fish with a DL model and then calculate the length of fish on that basis. Although this approach increases the workload, it is suitable for more complex images. The structural characteristics and computational capabilities of DL models can be fully exploited to achieve superior performances compared with other models. In addition, DL-based methods can eliminate the influence of fish overlap during length estimation.

The number of fish shoals can also provide valuable input for the development of intelligent systems. DL has shown comprehensive advantages in animal computing. To achieve automatic counting of fish groups under high density and frequent occlusion characteristics, a fish distribution map can be constructed using DL; then, the fish distribution, density and quantity can be obtained. These values can indirectly reflect fish conditions such as starvation, abnormalities and other states, thereby providing an important reference for feeding or harvest decisions.

The age structure of a fish school is another important input to fishery assessment models. The current method for determining fish school age structure relies on manual assessments of otolith age, which is a labor-intensive and expertise-dependent process. Using a DL approach, target recognition can instead be performed by using a pretrained CNN to estimate fish ages from otolith images. The accuracy is equivalent to that achieved by human experts and considerably faster.

Optical imaging and sonar are often used to monitor fish biomass. A DL algorithm can be applied to automatically learn the conversion relationship between sonar images and optical images, thus allowing a "daytime" image to be generated from a sonar image and a corresponding night vision camera image. This approach can be effectively used to count fish, among other applications.

3.8 Feeding decision-making

In intensive aquaculture, the feeding level of fish directly determines the production efficiency and breeding cost. In actual production, the feed cost for some varieties of fish accounts for more than 60% of the total cost. Thus, unreasonable feeding will reduce production efficiency, while insufficient feeding will affect fish growth. Excessive feeding also reduces the feed conversion efficiency, and the residual bait will pollute the environment. Therefore, large economic benefits can be gained by optimizing the feeding process. However, many factors affect fish feeding, including physiological, nutritional, environmental and husbandry factors; consequently, it is difficult to detect the real needs of fish.

Traditionally, feeding decisions depend primarily on experience and simple timing controls. At present, most research on making feeding decisions using DL has focused mostly on image analysis. By using machine vision, an improved feeding strategy can be developed in accordance with fish behavior. Such a system can terminate the feeding process at more appropriate times, thereby reducing unnecessary labor and improving fish welfare. The feeding intensity of fish can also be roughly graded and used to guide feeding. A combination of CNN and machine vision has proved to be an effective way to assess fish feeding intensity characteristics; the trained model accuracy was superior to that of two manually extracted feature indicators: flocking index of fish feeding behavior (FIFFB) and snatch intensity of fish feeding behavior (SIFFB). This method can be used to detect and evaluate fish appetite to guide production practices. Due to recent advances in CNNs, it would be interesting to consider the use of newer neural

network frameworks for both spatial and motion feature extraction. When combined with time-series information, such models may enable better feeding decisions. Based on this idea, considered both temporal and spatial flow by combining a three-dimensional CNN (3D-CNN) and an RNN to form a new dual deep neural network. The 3D-CNN and RNN were used to capture spatial and temporal sequence information, respectively, thereby achieving recognition of both feeding and nonfeeding behaviors. A comparison showed that the recognition results achieved with this dual-flow structure were better than those of either individual CNN or RNN models.

The studies discussed above focused primarily on images. However, many factors affect fish feeding; consequently, considering only images is insufficient. In the future, additional data, such as environmental measurements and fish physiological data, will need to be incorporated to achieve more reasonable feeding decisions.

	Model	Frame work	Data	Preprocessing augmentation	Transfer learning	Results	Performance comparison	
1	Maloy <i>et al.</i> (2019)	RNN	Tensor Flow	76 videos taken at a resolution of 224×224 pixels with RGB color channels and at 24 f/sec.	NA	N	Accuracy : 80%	NA
2	Zhou <i>et al.</i> (2019)	CNN	NA	Image was collected from a laboratory at 1 f/sec.	RST	N	Accuracy :90%;	SVM: 73.75%; BPNN: 81.25%; FIFFB: 86.25%; SIFFB: 83.75%

Figure 3.6 Feeding decisions

3.9 Water quality prediction

It is essential to be able to predict changes in water quality parameters to identify abnormal phenomena, prevent disease, and reduce the corresponding risks to fish. In real-world aquaculture, the water environment is characterized by many parameters that affect each other, causing considerable inconvenience in the prediction process. The traditional machine-learning-based prediction models lack robustness when applied to big data, resulting in a general lack of long-term modeling capability and generalizability, and they cannot fully reflect the essential characteristics of the data. In contrast, DL offers good capabilities in terms of nonlinear approximation, self-learning, and generalization. In recent years, prediction methods based on DL have been widely used.

Dissolved oxygen is one of the most important parameters and is important in intelligent management and control in smart fish farming. Due to the time lag between the implementation of control measures for dissolved oxygen and their regulation effects, it is necessary to predict future changes in dissolved oxygen to maintain a stable water quality. DL-based models such as a CNN or a deep belief network (DBN) can extract the relationships between quantitative water characteristics and water quality variables. Such models have been used to predict water quality parameters for the intensive culturing of fish or shrimp. The results show that the accuracy and stability of such models are sufficient to meet actual production needs.

However, most current methods have achieved good results only for short-term water quality predictions. In recent years, scholars have paid increasing attention to longer-term predictions. The key to long-term prediction is to extract the spatiotemporal relationships between water quality and external factors. Therefore, spatiotemporal models such as LSTM networks and RNNs are quite popular. For example, an attention-based RNN model can achieve a clear and effective representation of time-space relationships and its learning ability is superior to that of other methods for both short- and long-term predictions of dissolved oxygen. These models can be continuously optimized during the prediction process to improve their prediction accuracies.

The prediction of dissolved oxygen and other water quality parameters is

closely related to time. Attention-equipped, LSTM, DBN, and other DL models are able to mine the time sequence information well and achieve satisfactory results. Therefore, how to use DL models to avoid or reduce the negative impact of uncertainty factors on prediction results will be an important development direction in water quality prediction tasks.

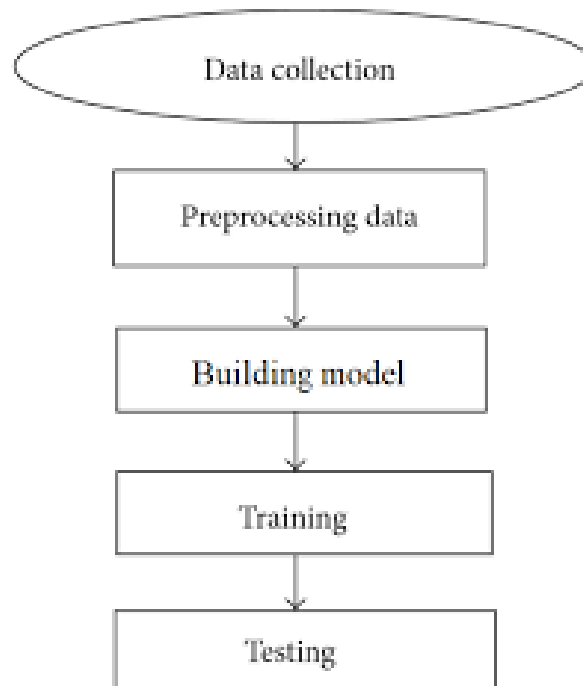


Figure 3.7 Steps involved in Water Quality Prediction

3.10 Technical details with Data

In DL, an annotated dataset is critical to ensure a model's performance. However, in practice, dataset construction is often affected by issues related to both quantity and quality. Before any images or specific features can be used as the input to a DL model, some effort is usually necessary to prepare the images through preprocessing and/or augmentation. The most common preprocessing procedure is to adjust the image size to meet the requirements of the DL model being applied. In addition, the learning process can be facilitated by highlighting the regions of interest or by performing background subtraction, foreground pixel extraction, image denoising enhancement and other steps to simplify image annotation. Additionally, some related studies have applied data augmentation

techniques to artificially increase the number of training samples. Data augmentation can be used to generate new labeled data from existing labeled data through rotation, translation, transposition, and other methods. These additional data can help to improve the overall learning process; and such data augmentation is particularly important for training DL models on datasets that contain only small numbers of images.

In addition, to avoid being constrained by the limited availability of annotation data, some scholars have directly used pretrained DL models to conduct fish classification, thus avoiding the need to acquire a large volume of annotated data. However, this approach has many limitations, such as negative transfer, learning or not learning from holistic images, and is consequently difficult to implement satisfactorily for specific applications; hence, it is typically suitable only for theoretical algorithm research.

3.11 Models framework

(1) Models. From a technical point of view, various CNN models are still the most popular (29 papers, 71%). However, 2 of the papers reviewed here use a GAN, 3 use an RNN, 2 use an LSTM, 2 use both an LSTM and a CNN, and 2 papers use a DBN and YOLO, respectively. Some CNN models are combined with output-layer classifiers, such as SVM and SoftMax or SoftMax classifiers.

(2) Frameworks. Caffe and TensorFlow are the most popular frameworks. One possible reason for the widespread use of Caffe is that it includes a pretrained model that is easy to fine-tune using transfer learning. Whether used for specific commercial applications or experimental research, the combination of DL and transfer learning helps to reduce the need for a large amount of data while saving significant training time. In addition, a variety of other DL frameworks and datasets exist that users can use easily. In particular, because of its strong support for graphical processing unit (GPU), the PyTorch framework has been used extensively in relatively recent literature.

(3) In fact, much of the research reviewed here uses transfer learning, which involves using existing knowledge from related tasks or fields to improve model learning efficiency. The most common transfer learning technique is to use

pretrained DL models that have been trained on related datasets with different categories. These models are then adapted to the specific challenges and datasets. Figure 3.8 shows a typical example of transfer learning. First, the network is trained on the source task with the labeled dataset. Then, the trained parameters of the model are transferred to the target tasks.

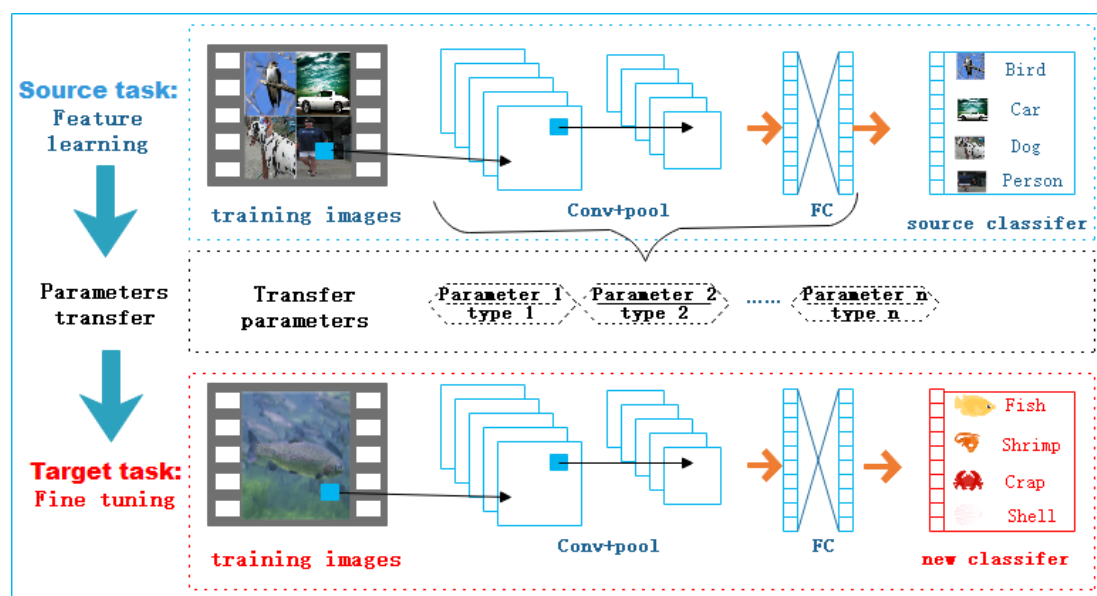


Figure 3.8 Typical example of transfer learning

(4) Model inputs. Although some studies use fish audio and water quality data, most of the model inputs are images (34, 83%). This situation reflects the significant advantage offered by DL in data processing, especially image processing. The inputs include public datasets such as the ImageNet dataset, the Fish4Knowledge (F4K) dataset, and the Croatian and Queensland University of Technology (QUT) fish datasets. Other datasets include data collected and produced in the field or obtained through Internet search engines, such as Google. Combining optical sensors and machine vision with DL systems provides possibilities for developing faster, cheaper and noninvasive methods for in situ monitoring and post-harvesting quality monitoring in aquaculture. However, whether these datasets consist of text, audio, or image/video data, they typically hold large volumes of data. Such large amounts of data are particularly important when the problem to be solved is complex or when the difference between adjacent classes is small.

(5) Model outputs. Among the models used for classification, the outputs range from 4 to 16 classes. For example, one study considers images of 16 species of fish, and another considers 4 types of fish sound files. Among the other papers, 13 targeted live fish recognition where the outputs were fish and non-fish; 7 were size or biomass estimations; 2 were quantifications of fish feeding intensity; 6 were water quality predictions; and 5 were behavior analyses. However, from a technical point of view, the boundaries for identification, classification, and biomass estimation based on these classification models are quite vague. In these papers, the output and input classes for each model are the same. Each output consists of a set of probabilities that each input belongs to each class, and the model finally selects the class with the highest output probability for each input as the predicted class of that input.

3.12 TENSOR FLOW

Tensor Flow is an open-source software library. Tensor Flow was originally developed by researchers and engineers working on the Google Brain Team within Google's Machine Intelligence research organization for the purposes of conducting machine learning and deep neural networks research, but the system is general enough to be applicable in a wide variety of other domains as well. The word Tensor Flow actually means! Tensor Flow is basically a software library for numerical computation using data flow graphs where:

- nodes in the graph represent mathematical operations.
- edges in the graph represent the multidimensional data arrays (called tensors) communicated between them

Chapter 4

MERITS AND DEMERITS

4.1 Advantages of deep learning:

The key advantage of DL in aquaculture is that DL models perform better than do the traditional methods. This may be because traditional machine learning algorithms require the manual feature extraction from images. Manually selecting features is a laborious, heuristic approach, and the effect is highly dependent on both luck and experience. In contrast, a DL algorithm can automatically learn and extract the essential features from images in a sample dataset. Such algorithms offer high accuracy and strong stability for irregular target recognition in complex environments, and they can effectively learn mappings and correlations between a sample and objects from that sample. In addition, useful features can be learned automatically using a general-purpose learning procedure

For example, in fish recognition, a DL model can effectively extract essential fish features. Such models have shown strong stability under challenging conditions such as low light and high noise, and they perform better than do traditional artificial feature extraction methods. In behavioral analysis research, a DL model can effectively address problems related to occlusion. In addition, a DL model can be used not only to monitor unknown objects or anomalies but also to predict parameters such as water quality.

Although DL models require more computing power and longer training times than do traditional methods (such as the SVM and random forest methods), after training is complete, the trained DL models are highly efficient at performing test tasks. For example, in a fish recognition study, using for 900,000 images, the training process lasted 8 days on a computer with 64 GB of RAM, an i7 CPU @3.50 GHz, and a Titan X GPU card. However, after training was complete, the recognition time for each frame was only 0.06 s. In a study by Ahmad *et al.* (2016), training the CNN model required 5~6 h without a GPU implementation. However, during testing, each fish image required only approximately 1 millisecond for classification, making this model fully compatible with real-time processing needs.

4.2 Disadvantages and limitations of deep learning:

At present, DL technology is still in a weak AI stage. While weak AI systems can simulate the functions of the mind through a computational system; however, they cannot yet artificially recreate a mind. The ability of DL models to constantly learn and improve is still very weak. In smart fish farming, DL models are used only as “black boxes”. Because DL models are excessively reliant on sample data and have low interpretability, they can typically gain experience only from a specific dataset. Moreover, when faced with unbalanced training data, most models will tend to ignore some important features.

Incomplete data. One of the most significant drawbacks of DL is the large amount of data required during training. For example, when using DL to identify fry size, not only are there many kinds of fish but their body shape and posture of each growth stage are also quite different, which

necessitates high requirements for data collection and DL training. However, in traditional fisheries, no such datasets exist, or the available datasets are not sufficiently comprehensive. Thus, in this initial stage, much basic data collection work remains to be done.

Although data augmentation technology can be used to add some labeled samples to an existing dataset, when dealing with complex problems (e.g., multiclass problems with high precision requirements), more diversified training data are needed to improve accuracy. Because data annotation is a necessary operation in most cases, some complex tasks require experts to annotate data, and such expert volunteers are prone to make mistakes during data annotation, especially for challenging tasks such as fish species identification. Furthermore, data preprocessing is often a necessary and time-consuming task in DL, whether for image or text data. In addition, some existing datasets do not fully represent the problems toward which they are oriented. Finally, in the field of smart fish farming, researchers do not have access to many publicly available datasets; thus, in many cases, they need to develop custom image sets, which can take hours or days of work.

High cost. Whether the people involved are AI technicians or farmers, a large number of sensors need to be deployed when collecting data, making the up-capital cost investment in the early-stage substantial. Another limitation is that DL models demand high levels of computing power; in fact, the available common CPUs are typically unable to meet the requirements of DL. Instead, GPUs and tensor processing units (TPUs) are the mainstream sources of computing power suitable for DL; consequently, the hardware requirements are very high, and the cost is also quite high. In the absence of expected results, it is more difficult to persuade farmers to invest in the intelligent breeding industry, which is true in every country.

In aquaculture farms, continuous observations of fish status are vital for managing the growth and health status of the fish. There is strong demand for automatic fish monitoring systems, as these could improve efficiency and reduce the labor requirements in the aquaculture industry. Such monitoring systems are also attracting attention for their potential to perform fundamental surveillance of fish resources for sustainable resource management and environmental conservation.

It is an important task to reliably detect and track multiple moving objects for video surveillance and monitoring. However, when occlusion occurs in nonlinear motion scenarios, many existing methods often fail to continuously track multiple moving objects of interest. In this report we propose an effective approach for detection and tracking of multiple moving fishes with occlusion. Moving targets are initially detected using a simple yet efficient block matching technique, providing rough location information for multiple object tracking. More accurate location information is then estimated for each moving object by a nonlinear tracking algorithm. Considering the ambiguity caused by the occlusion among multiple moving objects, we apply an unscented Kalman filtering (UKF) technique for reliable object detection and tracking. Different from conventional Kalman filtering (KF), which cannot achieve the optimal estimation in nonlinear tracking scenarios, UKF can be used to track both linear and nonlinear motions due to the unscented transfer.

Chapter 5

RESULTS AND DISCUSSION

Here pretrained model Inception V2 with resnet34 architecture network has been used, that is trained on more than a million images from the ImageNet database. Inception v2 uses a similar architecture to Inception v1, which involves using a series of convolutional layers with different filter sizes and pooling operations to extract features from input images. The network is 164 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299. However, Inception v2 introduces several modifications to the original architecture to improve its accuracy and efficiency. After that normalizing and reshaping the input video or images to required size to train, test and validation images. After the initialization of the model, multiple images have been taken to test the model

5.1 Training Module

Fish detection using Inception v2 and a frozen inference graph involves the following steps:

1. Collect and label a dataset of fish images: To train an Inception v2 model to detect fish, a dataset of fish images must be collected and labeled. The dataset should include images of fish from different angles, sizes, and species.
2. Train the Inception v2 model: The labeled dataset is used to train the Inception v2 model. During training, the model learns to identify the features of fish images and classify them into different fish species.
3. Export a frozen inference graph: Once the Inception v2 model is trained, a frozen inference graph can be generated. This involves exporting the trained model to a frozen .pb file, which contains all the necessary weights and operations required for inference.
4. Use the frozen inference graph for fish detection: The frozen inference graph

can be loaded into a Python script or application, and used to detect fish in new images or video streams. This typically involves passing the input images through the graph, which applies the learned features and outputs the detected fish species and their locations.

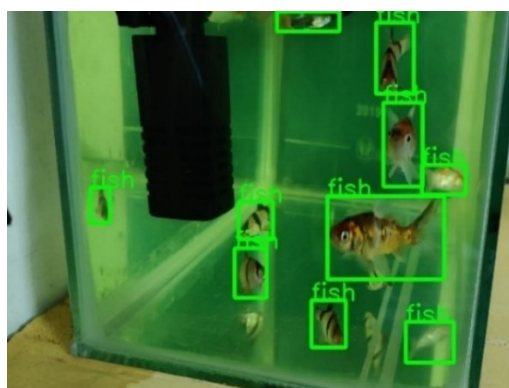
5. Overall, using Inception v2 and a frozen inference graph for fish detection can be an effective way to automate the process of identifying and classifying fish in different contexts, such as fisheries management, marine biology research, or aquaculture monitoring.

5.2 Fish Detection

The code has been developed through different phases by improving the code the implementation of code has come so far.

Phase - 1

In this phase the objective is to first detect the fishes in the tank, the output is shown by drawing a bounding around the fishes like shown in figure 5.1, the pictures of fishes are saved in a folder and the path of the is folder is given in the code.



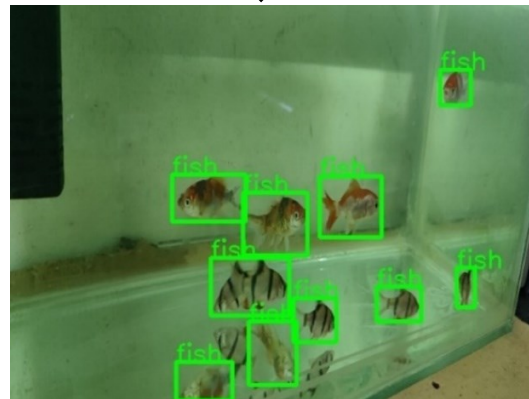


Figure 5.1 Fish Detection through images

Phase – 2

In next phase after testing phase 1 code, It is concluded that code is able to detect the fishes in the pictures so now it will be detecting the fishes through live camera. For this Reshaping and normalizing the input images for testing and validation. Loading dataset images from directory. Here, by normalization, which means changing x to $x/\|x\|$ it leads to a better performance because gradient descent converges faster after normalization. And reshaping the image size to required [244,244].



Figure 5.2 Fish detection through video

Phase – 3

In this phase some more features to the code are added, like displaying the **number of fishes, size, colour of the fishes, plotting the path taken by the fishes, dead or alive**. The output of the mentioned features is listed below.



Figure 5.3 Fish monitoring through live camera

In the final output for this model, here it gives the output as image (.jpg format) and small video format having features name printed on it. As it is seen in the above images, The live camera is given as input but in case there is no live camera detected then it automatically takes the saved fishes video as input, for that the path of video is given in the code and output mentions number of fishes, size, colour, dead or alive and path is traced in which direction the fish has been swimming. Since it is trained with more images and with efficient data set, the output will be more accurate.

5.3 Graphical Representation

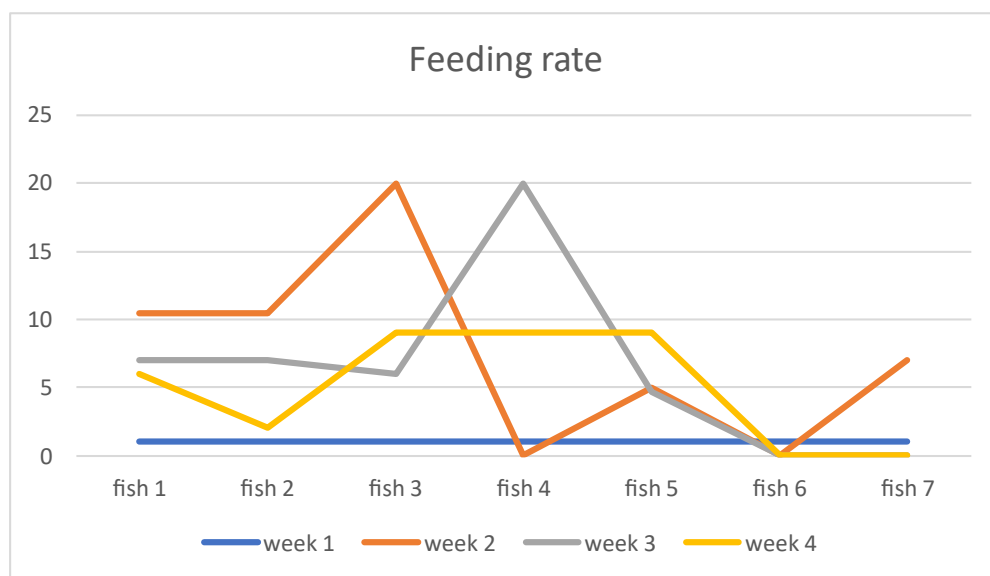


Figure 5.4 Graphical representation of feeding rate

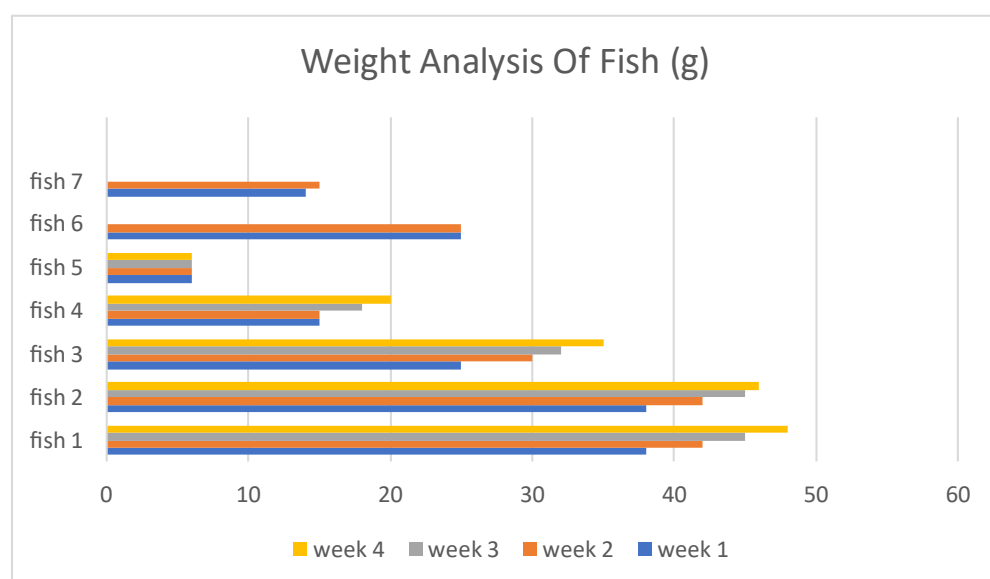
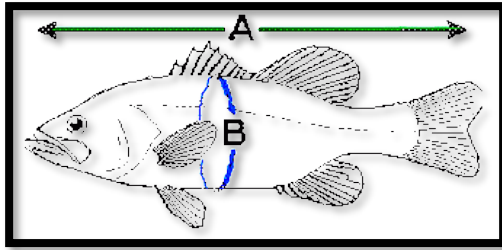


Figure 5.5 Graphical representation of Weight analysis

The weight of fishes has been noted on weekly basis and the results have been taken in the form of graph to analyze fish growth we can calculate the weight of the fishes based on the length of the fishes and changes depending upon the species of the fish.



$$\text{Length}^3 = \text{Length} \times \text{Length} \times \text{Length}$$

$$\text{Length}^2 = \text{Length} \times \text{Length}$$

$$\text{Girth}^2 = \text{Girth} \times \text{Girth}$$

Girth is the greatest distance around the body

Figure 5.6 Illustration to calculate Fish weight

The weight of the fish can be calculated using the above three formulas.

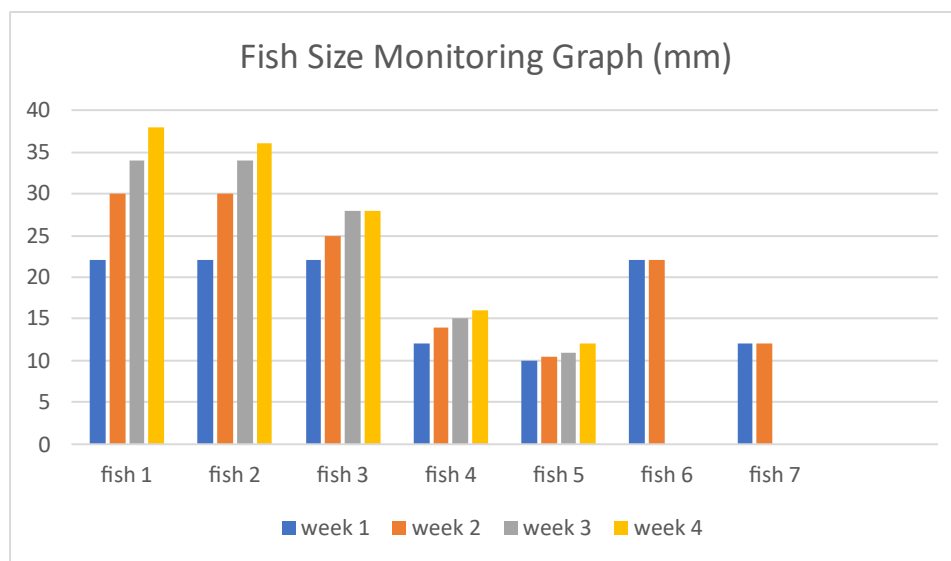


Figure 5.6 Graphical representation of Fish size

5.4 Final Analysis

	Fish No.	status	colour	size	Swimming behaviour	weight	Feeding rate
WEEK 1	1	Alive	Golden White	22 mm	Active	38 g	1 %
	2	Alive	Golden White	22 mm	Active	38 g	1 %
	3	Alive	Black	22 mm	Active	25 g	1 %
	4	Alive	Golden with Black stripes	12 mm	Active	15 g	1 %
	5	Alive	Grey	10 mm	Active	6 g	1 %
	6	Alive	Black	22 mm	Active	25 g	1 %
	7	Alive	Gold Fish	12 mm	Active	14 g	1 %
WEEK 2	1	Alive	Golden White	30 mm	Active	42 g	10.5 %
	2	Alive	Golden White	30 mm	Active	42 g	10.5 %
	3	Alive	Black	25 mm	Active	30 g	20 %
	4	Alive	Golden with Black stripes	14 mm	Active	16 g	6 %
	5	Alive	Grey	10.5 mm	Active	6 g	5 %
	6	Alive	Black	22 mm	Dull	25 g	0 %
	7	Alive	Gold fish	12 mm	Dull	15 g	7 %
WEEK 3	1	Alive	Golden White	34 mm	Active	45 g	7 %
	2	Alive	Golden White	34 mm	Active	45 g	7 %
	3	Alive	Black	28 mm	Active	32 g	6 %
	4	Alive	Golden with Black stripes	15 mm	Active	18 g	20 %
	5	Alive	Grey	11 mm	Slow	6 g	4.7 %
	6	Dead	-	-	-	-	-
	7	Dead	-	-	-	-	-
WEEK 4	1	Alive	Golden White	38 mm	Active	48 g	6%
	2	Alive	Golden White	36 mm	Active	46g	2%
	3	Alive	Black	28 mm	Normal	35 g	9 %
	4	Alive	Golden with Black stripes	16 mm	Normal	20 g	9 %
	5	Alive	Grey	12 mm	dull	6 g	9 %
	6	Dead	-	-	-	-	-
	7	Dead	-	-	-	-	-

Table 5.1 Status of the fishes

Chapter 6

CONCLUTION

6.1 Future technical trends of deep learning in smart fish farming:

The applications of DL in aquaculture will continue to expand or emerge. Various existing applications of DL in smart fish farming are covered in this review. The current application fields include live fish identification, species classification, behavioral analysis, feeding decisions, size or biomass estimation, and water quality prediction. Other possible application areas with great potential include fish disease diagnosis, aquatic product quality safety control and traceability, although no relevant research has been reported to date. Diseases and providing reasonable suggestions for managing identified diseases are expected to be an important application area, especially in relation to image processing.

Available dataset is becoming increasingly important. Datasets are an increasingly dominant concern in DL, sometimes even more important than algorithms. With the improved transparency of aquaculture information and the establishment of open fishery databases, researchers will be able to access a broader variety of sample data more easily. Although the number of publicly available datasets is still small, Appendix A lists some datasets that are freely available for download. Researchers can use these datasets to test their DL models or to pretrain DL models and then adapt them to more specific future challenges. Due to the limited dataset availability and the difficulty of collecting real data, methods of improving the recognition rate from small numbers of samples represents an inevitable direction for future research. Transfer learning can be used to ameliorate the problem of insufficient sample data. Additionally, the necessary preprocessing and augmentation of datasets will become increasingly important.

More advanced and complex models will continue to improve the performance of deep learning tasks. A combination model can be used to solve many of the problems faced by single models; as a result, more complex architectures will emerge. All types of DL models and classifiers as well as handcrafted features can be combined to improve the overall results. CNNs are widely used, but they

consider each frame independently and ignore the time correlations between adjacent frames. Therefore, it is necessary to consider models that can account for spatiotemporal sequences. It is expected that in the future, more methods similar to LSTM networks or other RNN models will be adopted to achieve higher classification or prediction performances that capitalize on the time dimension. Examples of such applications include estimating fish growth based on previous continuous observations, assessing fish water demands, developing measures to avoid disease, and fish behavior analysis. Such models can also be applied in environmental studies to predict changes in water quality.

Based on a review of the recent literature, the current applications can be divided into six categories: live fish identification, species classification, behavioral analysis, feeding decisions, size or biomass estimation, and water quality prediction. The technical details of the reported methods were comprehensively analyzed in accordance with the key elements of artificial intelligence (AI): data and algorithms. Performance comparisons with traditional methods based on manually extracted features indicate that the greatest contribution of DL is its ability to automatically extract features. Moreover, DL can also output high-precision processing results. However, at present, DL technology is still in a weak AI stage and requires a large amount of labeled data for training. This requirement has become a bottleneck restricting further applications of DL in smart fish farming. Nevertheless, DL still offers breakthroughs for processing text, images, video, sound and other data, all of which can provide strong support for the implementation of smart fish farming. In the future, DL is also expected to expand into new application areas, such as fish disease diagnosis; data will become increasingly important; and composite models and models that consider spatiotemporal sequences will represent the main research direction. In brief, our purpose in writing this review was to provide researchers and practitioners with a better understanding of the current applications of DL in smart fish farming and to facilitate the application of DL technology to solve problems in aquaculture.

6.2 Challenges

The recognition method based on deep learning was implemented by extracting rich feature information from video clips. We highlighted the movement behavior of fish in the feature image by fusing spatiotemporal features and motion features. The results show that our proposed method further improves the accuracy of behavior recognition and meets the needs of behavior classification in aquaculture.

However, fish behaviors are susceptible to external environmental stimuli, showing a series of complex behavior states. Therefore, many similar behavior fragments lead to the misjudgment of the model. The most significant is that both the feeding and frightening behaviors stimulated by the external environment exhibit the aggregation state of the fish school. This behavioral change involves the rapid movement of the fish to a certain position. The similarity of behavioral activity is the reason for the misjudgment of feeding behavior and frightening behavior. In addition to floating at the inlet of the circulating water, fish also exhibit slow swimming behavior under hypoxia. This inactive behavior often occurs under normal conditions, and its appearance is similar to hypoxic behavior. Therefore, the research should focus on how to extract deep feature information and accurately identify behaviors in different environments.

In our study, only five basic fish behaviors were identified, including feeding, water quality prediction, size or bio-mass calculation, species classification, and behavioral analysis. However, fish also exhibit higher-level behaviors such as fish reproduction and fighting in real farming. Reproductive behavior is an essential behavior to optimize the breeding level in aquaculture. We focused on the study of fish movement behavior, while reproductive behavior is difficult to distinguish from normal behavior. Fighting behavior is a competitive behavior in which two or more fishes compete for resources, but it is not easy to collect behavioral data. Furthermore, a general network is difficult to recognize multiple behaviors at the same time, which will reduce the confidence of the network prediction result. Therefore, future research will consider more types of behaviors and further improve the ability to predict multi-classification tasks. In the foreseeable future, the fusion of machine vision methods and acoustic imaging methods will realize the intelligent recognition of fish behavior in aquaculture.

6.3 Notable IEEE Standards committees and formats

<u>IEEE P80</u>	Guide for Safety in AC Substation Grounding
<u>IEEE 255</u>	Standard Letter Symbols for Semiconductor Devices, IEEE-255-1963
<u>IEEE 260</u>	Standard Letter Symbols for Units of Measurement, IEEE-260-1978 (now 260.1-2004)
<u>IEEE 488</u>	Standard Digital Interface for Programmable Instrumentation, IEEE-488-1978 (now 488.1)
<u>IEEE 519</u>	Recommended Practice and Requirements for Harmonic Control in Electric Power Systems
<u>IEEE 603</u>	Standard Criteria for Safety Systems for Nuclear Power Generating Stations
<u>IEEE 610</u>	Standard Glossary of Software Engineering Terminology
<u>IEEE 754</u>	<u>Floating point</u> arithmetic specifications
<u>IEEE 802</u>	<u>LAN/MAN</u>
<u>IEEE 802.1</u>	Standards for LAN/MAN bridging and management and remote media access control (MAC) bridging
<u>IEEE 802.2</u>	Standards for Logical Link Control (LLC) standards for connectivity
<u>IEEE 802.3</u>	<u>Ethernet</u> Standards for Carrier Sense Multiple Access with Collision Detection (CSMA/CD)
<u>IEEE 802.4</u>	Standards for token passing bus access
<u>IEEE 802.5</u>	Standards for token ring access and for communications between LANs and MANs
<u>IEEE 802.6</u>	Standards for information exchange between systems
<u>IEEE 802.7</u>	Standards for broadband LAN cable
<u>IEEE 802.8</u>	Fiber-optic connection
<u>IEEE 802.9</u>	Standards for integrated services, like voice.
<u>IEEE 802.10</u>	Standards for LAN/MAN security implementations
<u>IEEE 802.11</u>	Wireless Networking – " <u>WiFi</u> "
<u>IEEE 802.12</u>	Standards for demand priority access method
<u>IEEE 802.14</u>	Standards for cable television broadband communications
<u>IEEE 802.15.2</u>	Bluetooth and Wi-Fi coexistence mechanism
<u>IEEE 802.15.4</u>	Wireless Sensor/Control Networks " <u>ZigBee</u> "
<u>IEEE 802.15.6</u>	Wireless <u>Body Area Network</u> ^[17] (BAN)
<u>IEEE 802.16</u>	Wireless Networking – " <u>WiMAX</u> "
<u>IEEE 802.24</u>	Standards for Logical Link Control (LLC) standards for connectivity

IEEE 828	Configuration Management in Systems and Software Engineering
IEEE 829	Software Test Documentation
IEEE 830	Software Requirements Specifications
IEEE 854	Standard for Radix-Independent Floating-Point Arithmetic, IEEE-854-1987 (replaced by IEEE-754-2008 and newer)
IEEE 896	Futurebus
IEEE P1003.1	Portable Operating System Interface – – POSIX
IEEE 1016	Software Design Description
IEEE 1028	Standard for Software Reviews and Audits
IEEE 1044.1	Standard Classification for Software Anomalies
IEEE 1059	Software Verification And Validation Plan
IEEE 1073	Point of Care Medical Device Communication Standards
IEEE 1074	Software Development Life Cycle
IEEE 1076	VHDL – VHSIC Hardware Description Language
IEEE 1149.1	JTAG
IEEE 1149.6	AC-JTAG
IEEE 1180	Discrete cosine transform accuracy
IEEE 1233	System Requirements Specification
IEEE 1275	Open Firmware
IEEE 1284	Parallel port
IEEE P1363	Public key cryptography
IEEE 1364	Verilog
IEEE 1394	Serial bus – "FireWire", "i.Link"
IEEE 1471	software architecture / system architecture
IEEE 1541	Prefixes for Binary Multiples
IEEE 1547	Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces
IEEE 1584	Guide for Performing Arc Flash Hazard Calculations
IEEE 1588	Precision Time Protocol
IEEE 1609	Wireless Access in Vehicular Environments (WAVE)
IEEE P1619	Security in Storage Working Group (SISWG)
IEEE 1625	Standard for Rechargeable Batteries for Multi-Cell Mobile Computing Devices
IEEE 1666	IEEE Standard for Standard SystemC Language Reference Manual

IEEE 1667	Standard Protocol for Authentication in Host Attachments of Transient Storage Devices
IEEE 1701	Optical Port Communication Protocol to Complement the Utility Industry End Device Data Tables
IEEE 1800	SystemVerilog
IEEE 1801	Unified Power Format
IEEE 1849	IEEE Standard for eXtensible Event Stream (XES) for Achieving Interoperability in Event Logs and Event Streams
IEEE 1855	IEEE Standard for Fuzzy Markup Language
IEEE 1901	Broadband over Power Line Networks
IEEE 1906.1	Recommended Practice for Nanoscale and Molecular Communication Framework
IEEE 1914	Next Generation Fronthaul Interface Working Group
IEEE 1914.1	Standard for Packet-based Fronthaul Transport Networks
IEEE 1914.3	Standard for Radio Over Ethernet Encapsulations and Mappings
IEEE 2030	Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System (EPS), End-Use Applications, and Loads
IEEE 2030.5	Standard for Smart Energy Profile Application Protocol
IEEE 2050	RTOS for embedded systems standard
IEEE 2143.1	Standard for General Process of Cryptocurrency Payment
IEEE 2413	Standard for an Architectural Framework for the Internet of Things (IoT)
IEEE 2418.2	Approved Draft Standard Data Format for Blockchain Systems
IEEE 2600	Hardcopy Device and System Security (and related ISO/IEC 15408 Protection Profiles)
IEEE 3001.4	Recommended Practice for Estimating the Costs of Industrial and Commercial Power Systems
IEEE 7010	Recommended Practice for Assessing the Impact of Autonomous and Intelligent Systems on Human Well-Being
IEEE 12207	Information Technology – Software life-cycle processes
IEEE C37.2040	Standard Cybersecurity Requirements for Substation Automation, Protection, and Control Systems
IEEE Switchgear Committee	C37 series of standards for Low and High voltage equipment
IEEE Transformers Committee	C57 series of standards for the design, testing, repair, installation and operation and maintenance of transformers

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RESEARCH PAPER

Deep learning-based fish tank monitoring system for continuous fish health monitoring

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Abstract

Due to its rapid growth, deep learning (DL) technology is now being successfully used in a variety of sectors, including aquaculture. DL has a variety of effects on information and data processing in smarter fish farming, including new possibilities and challenges. Live fish identification, species categorization, behavioral analysis, food selection, size or biomass estimation, and water quality forecasting are among the uses of DL in aquaculture that are covered in this research. In addition, the efficacy of the DL approach used in smart fish farming is evaluated along with the data, algorithms, and performance. The review's conclusions show that DL's ability to automatically extract features is its most significant addition. However, there are still issues. For instance, deep learning (DL) training needs a sizeable amount of labelled data, which is still a relatively new development in AI. Stage and has turned into a bottleneck that prevents further DL applications in aquaculture because it needs a significant quantity of labelled data for training. However, DL continues to provide innovations for handling complicated data in aquaculture. In a nutshell, our goal is to give academics and practitioners a better grasp of the state-of-the-art in DL in aquaculture, which can be an excellent foundation for implementing smart fish farming applications.

Keywords: Deep learning; Smart fish farming; Advanced analytics; Aquaculture;

Introduction

The output of the world's fisheries increased to a new high of 171 million tonnes in 2016. To achieve the Food and Agriculture Organization of the United Nations (FAO) objective of creating a world free from hunger and malnutrition, 88% of this production must be eaten directly by people. (FAO, 2018). But as the world's population continues to expand, the strain on the fisheries will grow as well. (Merino et al., 2012; Clavelle et al., 2019).

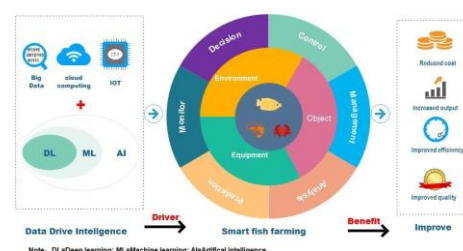


Figure 1. The role of deep learning and big data smart fish farming

A new scientific field known as "smart fish farming" aims to maximize resource utilization and advance sustainable aquaculture development by tightly integrating the Internet of Things (IoT), big data, cloud computing, artificial intelligence, and other contemporary information technologies. Additionally, a

new fishery production mode has finally been formed thanks to real-time data gathering, quantitative decision-making, intelligent control, precise investment, and personalized service. (Figure 1).

Information and data are the foundational components of smart fish aquaculture. The capacity to make choices with a scientific foundation will result from the aggregation and advanced analytics of all or some of the data. The vast quantity of data generated by smart fish farming, however, presents a number of difficulties, including multiple sources, multiple formats, and complex data. Information on the tools, the fish, the surroundings, the breeding procedure, and the people is gathered from a variety of sources. Text, image, and audio are some of the various forms. Different species, modes, and phases of cultured organisms are the cause of the data complexity. It is a very difficult job to deal with the above high-dimensional, nonlinear, and massive data. DL and its uses in smart fish farming are thoroughly reviewed in this article. The different DL forms come first. The technical details are briefly introduced after an overview of the various DL applications related to aquaculture that highlight the most recent developments in pertinent fields.

Design and Analysis

Block Diagram

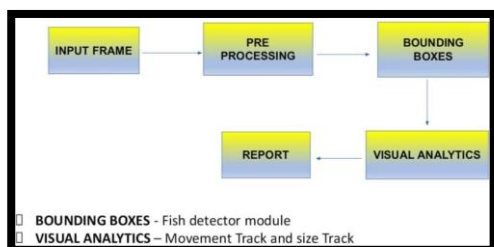


Figure 2. Layout of the project

The Inception-v2 neural network design is used for image classification jobs. It was created by Google in 2015 and represents an improvement over the initial Proposed method. One of the

main improvements in Inception-v2 is the use of batch normalization and RMSprop optimizer for faster and more precise training, as well as the inclusion of more network layers. The building also includes a brand-new "Inception-A" module for more efficient computing. Inception-v2 played a significant role in Google's successful entry for the 2015 ImageNet Large Scale Visual Recognition Challenge.

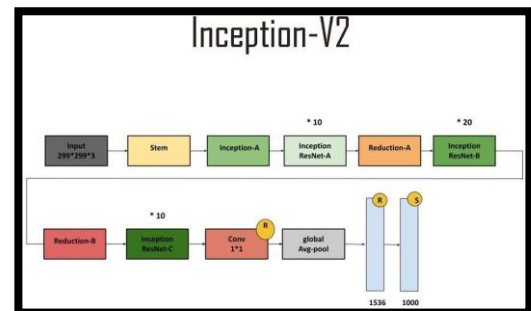


Figure 3. Flow chart of Inception V2

Hardware description

- Raspberry Pi
- Raspberry Pi Camera Module
- We use Gpu(Graphic processing unit) to train our model

What is Raspberry Pi why do we use it?

The Raspberry Pi is a compact, inexpensive single-board computer created to support the instruction of fundamental computer science in educational institutions and underdeveloped nations. It was created in 2012 by the Raspberry Pi Foundation in the UK. Due to its adaptability and low cost, Raspberry Pi is well-liked by researchers, instructors, and hobbyists. Media centers, home automation, networking, gaming, and programming are just a few of the many tasks it can be used for.



Figure 4. Raspberry Pi

Raspberry Pi is also a useful tool for researchers who use it to create inexpensive, low-power devices for scientific experiments and educators who use it to teach computer science and other topics in classrooms. With a keyboard, mouse, and display, Raspberry Pi can be used as a stand-alone computer. It can also be used as an embedded computer with a more focused purpose that is controlled by another device

Raspberry Pi Camera Module

A single-board computer called the Raspberry Pi can be equipped with a tiny camera called the Raspberry Pi Camera Module. Since its initial release in 2013, additional versions have been added, including the v2 and the High Quality (HQ) Camera. A variety of tasks, including time-lapse photography, wildlife photography, security cameras, and more, can use the camera module. The camera module can take still pictures with a quality of up to 3280x2464 and videos with resolutions of 1080p30, 720p60, and 640x480p90.



Figure 5. Pi Camera Module

The module can also be used to build custom software for the camera and is compatible with Python and other programming languages. This makes it an excellent tool for computer vision

tasks like face and object recognition.

Working.

Fish detection is a task in computer vision and machine learning that involves identifying fish in images or videos. There are several different approaches to fish detection, but some common methods include:

Haar cascades: Haar cascades are a type of object detection method that uses a series of simple classifiers to detect objects in images. They can be trained to detect fish by using a dataset of positive and negative images of fish.

Deep learning: Deep learning is a type of machine learning that uses neural networks to learn features and patterns in data. Convolutional neural networks (CNNs) are a popular type of deep learning model that can be used for fish detection. CNNs can be trained on large datasets of fish images to learn the features that are unique to fish and can be used to detect fish in new images.

YOLO: YOLO (You Only Look Once) is a real-time object detection system that uses a single neural network to detect objects in images. It can be trained to detect fish using a dataset of fish images.

Faster R-CNN: Faster R-CNN is a deep learning-based object detector that uses a region proposal network (RPN) to generate region proposals and a CNN to classify the objects in the regions. It can be trained to detect fish by using a dataset of fish images.

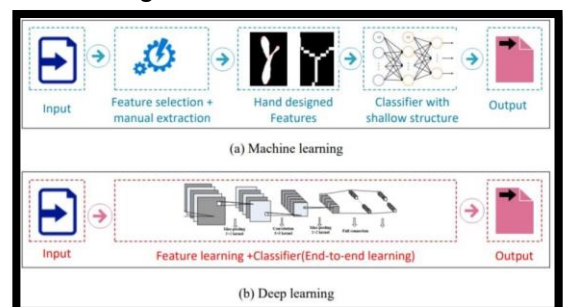


Figure 6. Deep Learning and Machine Learning

RetinaNet: RetinaNet is a single-stage object detector that uses focal loss to address the problem of imbalance between foreground and background classes.

These methods can be applied to both still images as well as videos, and the performance of these methods varies based on the dataset and the specific problem.

Working on Live detection

A job in computer vision and machine learning called "fish live video detection" entails finding and following fish in real-time video streams. Fish live video detection can be done in a variety of ways, but some popular techniques include:

Optical flow: This technique tracks the motion of moving objects in a video feed by examining the variation in pixel intensity between adjacent frames. By identifying the movement of fish in the video, optical flow can be used to monitor fish in live video streams.

Deep learning-based techniques: Fish can be found and followed in real-time video feeds using deep learning-based techniques like CNNs and RNNs. RNNs can be used to monitor the fish over time, while CNNs can be trained on large datasets of fish images and videos to learn the features specific to fish.

Multi-object tracking: Using a combination of object detection and data association methods, multi-object tracking is a technique for tracking numerous objects in a video stream. Several fish can be tracked using this technique in a stream of live footage.

Machine learning-based methods: Fish detection in real-time video feeds can also be accomplished using machine learning-based techniques like Random Forest, SVM, KNN, etc. To understand the characteristics specific to fish, these methods are trained on a dataset of fish images or videos.

Real-time methods: Fish detection in real-time video feeds can also be accomplished using machine learning-based techniques like Random Forest, SVM, KNN, etc. To understand the characteristics specific to fish, these methods are trained on a dataset of fish images or videos.

These methods can be applied to live video streams and the performance of these methods vary based on the dataset and the specific problem. The choice of method will depend on the requirements of the specific application and the resources available for the implementation.

Results

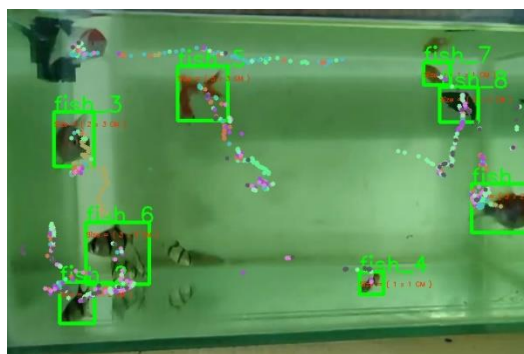
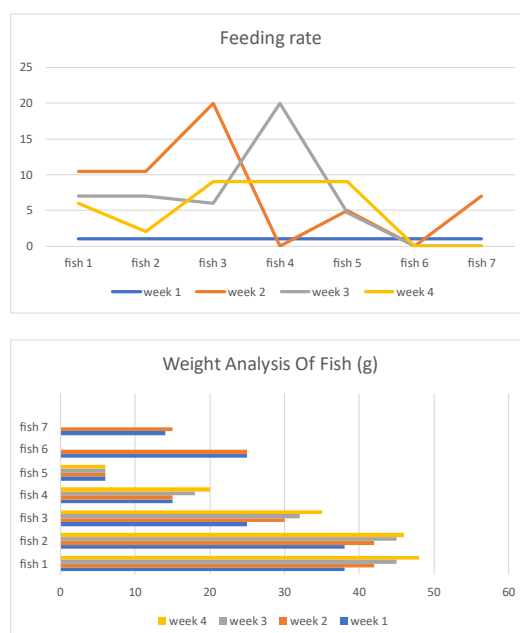
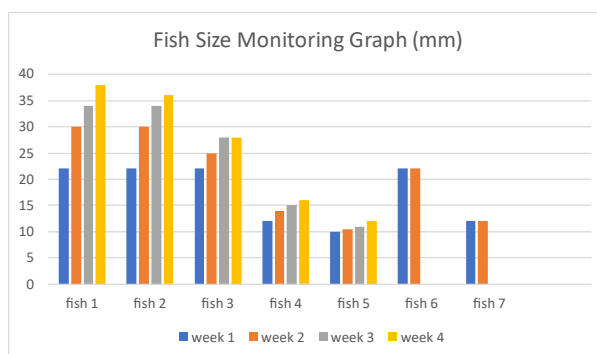


Figure 7. Fishes detected in Fish Tank using raspberry Pi and camera





	Fish No.	status	colour	size	Swimming behaviour	weight	feeding
WEEK 1	1	Alive	Golden White	22 mm	Active	38 g	1 %
	2	Alive	Golden White	22 mm	Active	38 g	1 %
	3	Alive	Black	22 mm	Active	25 g	1 %
	4	Alive	Golden with Black stripes	12 mm	Active	15 g	1 %
	5	Alive	Grey	10 mm	Active	6 g	1 %
	6	Alive	Black	22 mm	Active	25 g	1 %
	7	Alive	Gold Fish	12 mm	Active	14 g	1 %
WEEK 2	1	Alive	Golden White	30 mm	Active	42 g	10.5 %
	2	Alive	Golden White	30 mm	Active	42 g	10.5 %
	3	Alive	Black	25 mm	Active	30 g	20 %
	4	Alive	Golden with Black stripes	14 mm	Active	16 g	6 %
	5	Alive	Grey	10.5 mm	Active	6 g	5 %
	6	Alive	Black	22 mm	Dull	25 g	0 %
	7	Alive	Gold fish	12 mm	Dull	15 g	7 %
WEEK 3	1	Alive	Golden White	34 mm	Active	45 g	7 %
	2	Alive	Golden White	34 mm	Active	45 g	7 %
	3	Alive	Black	28 mm	Active	32 g	6 %
	4	Alive	Golden with Black stripes	15 mm	Active	18 g	20 %
	5	Alive	Grey	11 mm	Slow	6 g	4.7 %
	6	Dead	-	-	-	-	-
	7	Dead	-	-	-	-	-
WEEK 4	1	Alive	Golden White	38 mm	Active	48 g	6 %
	2	Alive	Golden White	36 mm	Active	46g	2 %
	3	Alive	Black	28 mm	Normal	35 g	9 %
	4	Alive	Golden with Black stripes	16 mm	Normal	20 g	9 %
	5	Alive	Grey	12 mm	dull	6 g	9 %
	6	Dead	-	-	-	-	-
	7	Dead	-	-	-	-	-

Figure 8. Status of Fishes

Future Scope

Aquaculture will continue to use DL in new or expanding ways. This review covers a number of DL's current uses in smart fish farming. Fish identification in real time, species classification, behavioral analysis, feeding choices, size or biomass estimation, and water quality prediction are all current application

areas. While no relevant research has been reported on diseases, other potential application areas with great potential include fish disease diagnosis, aquatic product quality safety control, and traceability. However, these application areas are expected to be crucial, particularly regarding image processing.

Conclusion

The fundamental components of artificial intelligence (AI), namely data and algorithms, underwent a thorough analysis of the technical details of the described methods. The greatest addition of DL is its ability to automatically extract features, according to performance comparisons with conventional techniques based on manually extracted features. Additionally, DL can produce high-precision computing outcomes. However, since DL technology is still in its early stages of AI development, it needs a lot of labelled data to be trained. This prerequisite has turned into a barrier that prevents more DL applications in smart fish farming. However, DL continues to make strides in the processing of text, images, video, sound, and other types of data, all of which can be extremely helpful in the application of smart fish farming. Future DL research is anticipated to focus primarily on composite models and models that take spatiotemporal sequences into account, as well as to broaden into new application areas like the detection of fish diseases. In a nutshell, our goal in writing this review was to aid in the application of DL technology to practical aquaculture issues and to give academics and practitioners a better grasp of the current applications of DL in smart fish farming.

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