Comparative Analysis of Biomass Estimation Methods in Aquaculture: A Review

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Abstract
India is the third largest producer of fish in the world, behind China and Indonesia. Andhra Pradesh is the top state in India when it comes to fish output. Around 68 percent of the overall fish production is attributed to the aquaculture sector. Aquaculture contributes 1.07 percent to the nation's Gross Domestic Product (GDP). India is expected to use 1.6 million tonnes of fisheries by 2025. However, due to recent changes in local weather conditions, there has been a decrease in the productivity of aquatic ecosystems. The fish population in a concentrated aquaculture environment may provide useful data for the development of effective factory management systems. Advanced technologies play a vital role in augmenting the quality of products and raising the efficiency of production in aquaculture. Integrating automated fish identification technologies will allow precision farmers to attain enhanced efficiency and scientifically controlled output. Computer vision methods, a crucial domain of artificial intelligence, have emerged as a potent tool for automated fish detection. This is feasible because to the extensive utilisation and availability of contemporary information technology, including the internet of things, big data, and camera devices. Currently, it is often used to estimate biomass. Nonetheless, the creation of computer vision models for fish recognition encounters several obstacles, including varying illumination, diminished contrast, substantial noise, deformed fish forms, frequent blockage, and shifting backdrops. This work conducts a thorough investigation of biomass estimate for fish identification in several application situations.

1. Introduction

Evaluating the number of fishes is crucial for the successful management of fisheries and the preservation of marine ecosystems. Gaining comprehension of fish populations in their native habitats, such as oceans and freshwater bodies, is crucial for preserving ecological equilibrium and mitigating the risk of over fishing. Accurate assessment of the stock of cultivated fish is crucial in aquaculture for calculating optimal feeding levels, reducing water pollutants, and safeguarding fish well-being. Automation, namely in the task of counting items, not only alleviates the workload but also improves precision in quantifying and monitoring the density of fish. This enables more effective management of aquaculture practices, ranging from tank maintenance to tracking fish yield and transportation. Estimating animal abundance is an essential aspect of sustainable practices and efficient operations in both wild and managed environments. The fish aquaculture distribution, as seen in Figure 1, illustrates the respective proportions derived from aquaculture and wild capture in oceans and inland water bodies. During the past twenty years, the aquaculture sector has experienced significant growth, resulting in an increase in its share of India's fish production from one-third to half [1]. Projections from the Food and Agriculture Organisation (FAO) of the United Nations indicate that aquaculture is anticipated to contribute almost two-thirds of India's overall fish output by the year 2030.

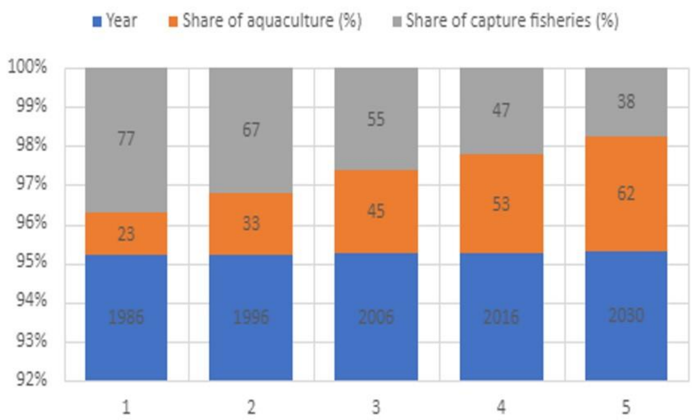

Figure-1 Source FAO (food & agriculture organisation of UN)

2.Theories related to Biomass Estimation

Historically, fish population assessments in aquaculture have depended on manual techniques or statistical modelling. However, these methods can be time-consuming and prone to errors due to assumptions made about the distribution of fish populations. On the other hand, the adoption of automated fish population monitoring enhances accuracy and decreases the reliance on labour intensive approaches. The various biomass estimation techniques can be seen as in Figure-2.

2.1. Biomass Estimation

The biomass data of aquaculture organisms is a crucial statistic commonly utilised in aquaculture to determine species classification, optimise feeding methods, estimate production, and more. The accurate evaluation of fish biomass serves as the basis for successful fisheries management and the implementation of sustainable fish production systems. The conventional method for obtaining fish biomass statistics involves identifying instances of recurrent fishing activities. Nevertheless, this method often subjects the fish to stress and physical harm, which negatively impacts their general health and welfare. Moreover, it relies on human will, which is no longer congruent with the standards of advanced aquaculture. Machine learning in fisheries offers novel opportunities for intelligent aquaculture. Simultaneously, the amalgamation of machine vision and machine learning enables more accurate predictions of fish size, weight, numbers, and other biological characteristics.

2.1.1. Size estimation

Multiple scholars have examined algorithmic methodologies for forecasting fish scale, predominantly utilising datasets such as ImageNet and the Atlantic fish dataset. Researcher devised a revolutionary R-CNN version with innovative architectures to forecast the length of European bass. Furthermore, the author employed OpenCV to calculate and enhance precision in order to address picture distortion problems. The findings indicated a mean deviation percentage of 2.2% [2]. It is important to mention that this model is mainly designed for perch fish and does not include situations when fish may overlap, which restricts its practical use. The researcher employed the Mask RCNN model together with local gradient technology to accurately determine the length of several fish species in the North Atlantic, taking into account situations when fish overlap with each other as well as situations where they do not. The final outcome yielded precise fish segmentation, with mean Intersection over Union (IoU) scores of 0.79 for cases where fish overlapped and 0.89 for cases where fish did not overlap. Although this technique is highly effective in handling huge datasets, it struggles to retain accuracy when dealing with smaller sample sizes. In order to tackle this problem, researcher used a Convolutional Neural Network (CNN) model with transfer learning to predict the length of fish in pond fish populations that had little sample data available. The results confirmed the model's efficacy, demonstrating an impressive accuracy rate of 93.93%. Moreover, the application of versatile camera technology has yielded encouraging outcomes in the estimation of fish body length. In their study, they employed a stereo vision system to determine the body length of Atlantic bluefin tuna. The experimental margin of error for their measurements was 3% [3].

2.1.2. Weight estimation

In the domain of fish weight estimation, researchers largely depend on the distinctive attributes of fish frame designs to provide accurate estimates. They employ image processing algorithms to extract data such as fish size, back geometry, and frame proximity, which adds to a full quality evaluation. The researcher Employed a hybrid approach of linear regression and convolutional neural network (CNN) to forecast weight based on the analysis of fish frame area, resulting in a notably high level of accuracy in their predictions. In the context of infrared mirrored image structures, infrared light is well-suited for capturing fish pictures in low-light conditions, maintaining stability without the reliance on external illumination. In addition, this infrared technology is utilised for the purpose of assessing the quality of fish. In their study, the researcher employed infrared light for fish photography and subsequently utilised RF (Random-forest) and SVM (Support vector machine) models to forecast the geometric characteristics of the fish's lower back. This approach effectively resolved the challenges associated with various illumination conditions. Nevertheless, these models have limitations in their capacity to capture photos at a precise distance and accurately estimate the foundation of a fish, leading to notable restrictions. researcher suggested a technique that integrates PCA-CF with a neural network to mitigate the impact of distance inconsistencies on the accuracy of first-class estimate, therefore addressing the deficiency in the purchase strategy. This technique was validated through the use of real-world data. Regardless of these advancements, the model continued to have challenges in accurately predicting the quantity of fish schools and had some constraints [4].

2.1.3. Counting

Counting in aquaculture has several challenges. Firstly, the devices themselves provide inherent difficulties, such as issues related to object transparency, variations in object shape and size, and complications arising from overlapping caused by motion. Additional complexities, however, occur from the surrounding environment, which encompasses interference problems, disturbances caused by water flow, and the complicated composition of the underwater terrain. This literature review study presents a concise overview of frequently employed automated counting techniques in the field of aquaculture. Optical sensing technologies are notable for their simplicity and directness, making them a dependable choice that can be seamlessly included into transfer pipelines or other devices. By employing image processing techniques and computer vision technologies, which are known for their non-invasive nature, it has been demonstrated that they can effectively and accurately count items in aquaculture in a timely manner. Recent advancements entail the use of machine learning and deep learning in computer vision, enhancing the capabilities of object recognition and detection. Moreover, acoustic technology is now employed in aquaculture for the purpose of object counting, namely in the evaluation of fish populations in lakes and rivers [5]. These acoustic methods, relying on hydroacoustic and acoustic imaging, show effectiveness even in challenging and murky environments. These acoustic methods, relying on hydroacoustic and acoustic imaging, exhibit effectiveness even in challenging environments like murky and dim water. This research assesses counting methodologies utilising several techniques and criteria, as seen in Figure-2.

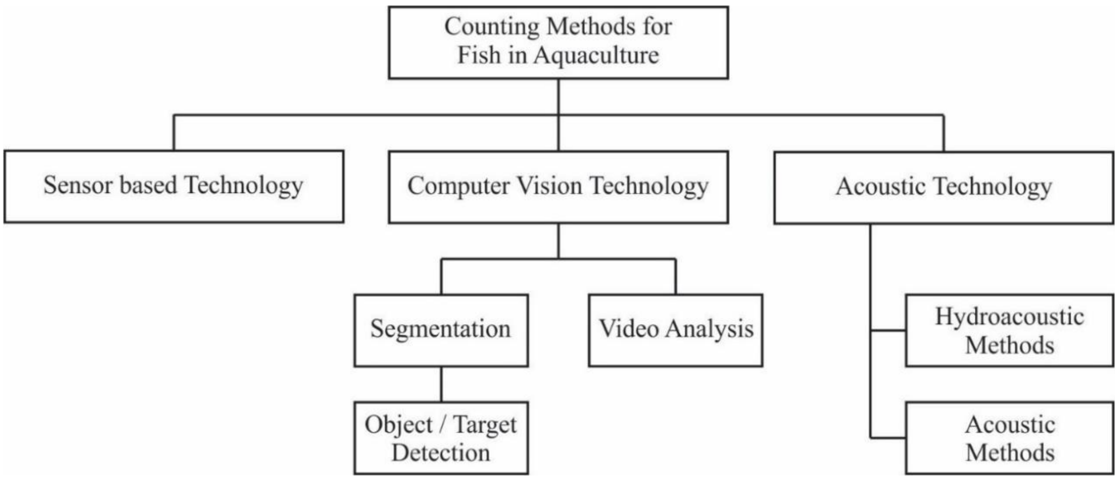

Fig-2 Various types of fish counting methods

3. Various types of fish counting methods

Fish counting in aquaculture plays a crucial role in managing stock levels, optimizing feeding schedules and monitoring overall health and welfare. The automated fish counting methods have emerged as a more accurate and less invasive alternative. These methods include sensor-based technologies, computer vision and acoustic technologies.

3.1. Counting based on sensor technology

The magnitude of aquaculture has conventionally been ascertained by quantifying the aggregate number of organisms to compute the harvest burden. In their study, researcher employed a weighing apparatus to measure the weight of roasted seedlings. Nevertheless, this method is imprecise due to the diverse dimensions and mass of the fish, and it might pose a risk to the fish's well-being. The efficacy of optical counters is constrained, especially in turbid water. The precision of fish counts may be compromised when a small number of fish pass through the pipeline, leading to an underestimation, or when fish move back and forth, resulting in an overestimation. The researcher employed a combination of non-imaging optics and image processing techniques to enhance optical systems for fish counting, enabling them to effectively address complex situations. Their approach significantly decreased the costs associated with detecting and counting, while also mitigating the impact of low signal-to-noise ratios resulting from fluctuations in water levels. An integrated system, utilising a Raspberry Pi as its core, along with a fixed-focus lens, enabled the accurate counting of two ornamental fish species in an aquarium. The fish ranged in size from 0.5 to 2.3 cm. The counting process achieved an exceptional level of accuracy, ranging from 94% to 98% [6].

3.2. Counting based on computer vision technology

Computer vision technology allows for non-invasive and accurate detection of organisms in aquatic animals, unlike sensor-based counting methods that often require measures to prevent fish intrusion and may introduce errors related to fish cover penetration and sensor exit from the surface. Computer vision is predominantly employed in aquaculture management for the purpose of estimating stock or biomass. This is achieved using two primary computing techniques: image processing and video analysis. Table-1 provides a comprehensive overview of the specific methods. The task of identifying and quantifying objects in underwater video and photos presents difficult circumstances and problems owing to a multitude of factors. Examples of them include a poor evaluation, diminishing brightness, inconsistent illumination, disturbance from water flow sounds, and the existence of ocean snow. The transmission of light through water results in substantial reduction in intensity, leading to the appearance of distant objects in the picture as being out of focus. Moreover, the many types of devices, the possibility of blockage caused by nearby devices, and the challenges of overlapping all add to the lack of precision in the images. While a camera may naturally capture two-dimensional (2D) pictures, it is inevitable to encounter the problem of filters or other things obstructing the view. Stereo vision is employed to collect three-dimensional (3D) object data in order to reduce interference and enhance accuracy. Underwater optical instruments, such as underwater vision devices, can be employed to record video of tuna moving from fish nets to floating traps, facilitating the process of measuring and assessing their numbers. A trawl-based underwater stereo camera has been developed specifically for capturing low-contrast and low-frame-rate videos, which aids in the evaluation of fish population. When there is a high concentration of fish, employing a three-dimensional image generated by binocular vision can help solve the issue of objects being obstructed from view [7].

TABLE-1 Introduction of several counting techniques and data set gathering

Object	Counting mechanism	Acquisition of data set	Reference
Aquatic vertebrate	Utilising the Kalman filter and the Hungarian technique for tracking purposes.	The underwater footage was acquired from the website	Sharif (2015)
Gilled vertebrate	The method used to monitor many objects relies on deformable multiple kernels.	Subaquatic mobile video footage captured in diverse settings and habitats	Chuang (2017)
Finned vertebrate	A system that combines a deep convolutional neural network with a 3D Kalman filter for tracking purposes.	Data sets of stereo images taken by a camera with two lenses	Huang (2019)
Aquatic vertebrate	Extended Kalman filtering is employed for object tracking, in combination with the nearest neighbour technique.	Acquisition of fish data using Dual Frequency Identification Sonar (DIDSON)	Jing (2017)
Pisces	Utilising edge detection and watershed segmentation for SVM classification.	An adaptive resolution imaging sonar has produced a sonar picture with exceptional clarity and detail.	Shahrestani (2017)

3.2.1. Counting by image processing

Fish counting using image processing represents a transformative approach in aquaculture management. By harnessing the power of digital imaging technology, fish counting becomes more accurate, efficient and non-invasive. One of the key advantages of fish counting by image processing is its scalability. It allows for the rapid assessment of large populations across various aquaculture settings from ponds and tanks to offshore farms. This scalability enhances productivity and facilitate better decision making in resource allocation and stock management.

3.2.1.1 Counting based on segmentation

Object segmentation is a crucial method for differentiating the item of interest from the background using intensity measurements. Blob counting is a technique employed to determine the quantity of objects by calculating the distinct zones of interest or potential candidates that have been separated from the background. Table-2 provides a concise overview of the four primary methods utilised for segmenting items for counting, along with their advantages and disadvantages. The utilisation of grey value-based threshold segmentation is a reliable and extensively employed technique for calculating regions in fish counts. Researcher created an embedded device that utilises threshold segmentation and morphological processing to accurately identify small-sized fish (0.5 to 2.33 cm) in aquariums, regardless of the illumination conditions. In a similar manner, another researcher employed the edge method to categorise prawn fry based on their developmental stage. They implemented a series of morphological processing steps to minimise the occurrence of counting a single item several times when it is separated into many interconnected domains. They have utilised adaptive threshold segmentation and portion identification techniques to analyse the phase and composition of barbecue. Simultaneously, they examined the behaviour and responses of fish to artificial lights of several spectral bands [9].

Edge detection is a rudimentary method of segmenting an image with the goal of identifying the boundaries of things inside it. This approach exploits the phenomenon that pixel values exhibit greater variability along the edges of objects compared to their interior positions. An edge detector is analogous to a high-pass filter since it identifies contours or edges distinguished by abrupt variations in luminosity. They have employed the Sobel Operator to detect the boundaries of fish, enabling them to estimate the presence of fish in complex backgrounds using auditory pictures. The Sobel Operator, being a first-order differential operator, is particularly effective in scenarios characterised by minimal noise and a small grey gradient. In order to address the difficulties caused by limited visibility underwater due to light absorption and scattering, researcher employed a blob detector based on the Laplacian of Gaussian (LoG) method, combined with Candy aspect contours detection, to accurately identify fish blobs. This strategy facilitated the evaluation of the fish population. The Candy side detector was selected over the Sobel detector due to its higher capability in detecting slender edges [10]. In a similar manner, one the researcher employed wavelet analysis following watershed segmentation to isolate fish Regions of Interest (ROIs) from video frames. Although part detectors are effective in recognising male or female regions of interest (ROIs) in aquaculture photos, they can be vulnerable to noise interference. Figure-3 provides flow diagram of fish tracking.

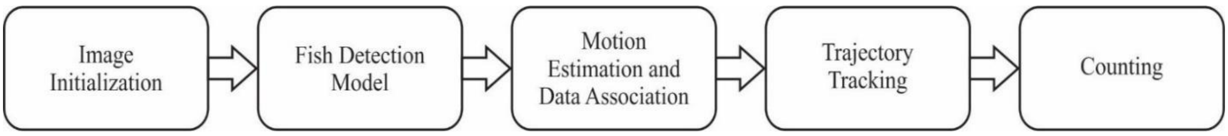

Fig-3 Flow diagram for fish tracking

TABLE-2 Different segmentation methods

Methodology	Object	Processing speed	Advantages	Disadvantages	References
Threshold segmentation	Aquatic vertebrate	Rapid	Execution is straightforward and effortless.	When evaluating, just take into account the numerical value of each pixel.	Dwi, Slamet, and Solahudin (2018).
Ostu threshold segmentation	Pisces	Rapid	Optimal threshold determination based on adaptability	Processing multi-threshold photos is challenging.	by Labuguen et al. in 2012
Edge segmentation	Gilled vertebrate	Rapid	Capable of adjusting to variations in illumination	Under some circumstances, it may be susceptible to noise.	Fabic, Turla, Capacillo, David, and Naval (2013) and Shahrestani, Bi, Lyubchich, and Boswell (2017)
Watershed algorithm	Fish roe	Intermediate	Discovering connected domains is straightforward.	Excessive noise can lead to the phenomenon of over-segmentation.	Duan et al. in 2015

3.2.1.2 Counting based on object detection

The utilisation of class techniques is a crucial element in the identification of fish goals. The You Only Look Once (YOLO) approaches, which are a renowned single-level framework, have been extensively employed for fish recognition. The researcher employed the YOLOv3 version to identify fish in hydropower applications of the modern power era. Their main focus was to evaluate the precision of fish recognition using MHK power across three datasets. The analysis showed an average mAP score of 0.5392 [11]. They enhanced the YOLOv3 model by substituting the Darknet-53 network with MobileNet, resulting in an augmented function extraction rate. After the version was created, a thorough selection of records was made from ImageNet to enhance the extraction of certain fish characteristics, with the ultimate aim of enhancing accuracy. The results indicated that the model surpassed YOLOv3 in terms of accurately detecting fish with a high level of precision [12].

In recent years, there has been an increasing fascination with utilising Convolutional Neural Network (CNN) models for fish detection. Researcher utilised the GoogLeNet architecture to extract fish attributes and identified coral fish using the softmax classification method. The author employed a decision rule to enhance precision, resulting in an impressive accuracy rate of 94.9%. It increased the number of convolutional layers in the CNN architecture to improve the accuracy of fish popularity and classification. This enhancement led to a maximum accuracy of 96.63%. In addition, the enhanced Convolutional Neural Network (CNN) utilised the R-CNN and LSTM (Long short-term memory) architectures to detect fish. In order to enhance the speed of fish identification while maintaining high accuracy utilised Faster R-CNN techniques to detect fish. They trained the network using the pre-trained Zeiler and Fergus model and employed a cascade architecture including R-CNN and LSTM models to enhance fish identification. This approach led to an improvement in the accuracy of CNN-based detection. Significantly, when compared to Faster R-CNN, this method exhibited superior accuracy, recall, and F-Score. Concurrently, researchers examined fish recognition algorithms specifically developed for low-resolution photo sets [13]. In this regard, researcher has introduced three historical past extraction techniques: Gaussian Mixture Model (GMM), Kernel Density Estimation (KDE), and the Visual Background Extractor (ViBe). These algorithms surpass fish in detecting diverse items by generating background subtraction (BS), resulting in empirically verified accuracies of 80% and 60% for the two datasets, respectively. In contrast, they have employed a more robust Gaussian Mixture Model (GMM) to detect fish in obscured backgrounds. The researchers employed Gaussian Mixture Model (GMM) along with 3-frame difference technology for target identification. This strategy led to improved precision in detecting fish, surpassing the performance of previously mentioned methods [14]. In addition, utilization of the transfer learning techniques to detect fish, despite the significant challenges posed by the underwater environment. By refining the acquired parameters of AlexNet using real-world data, they achieved a technique with an accuracy of 99%. Collectively, these methodologies provide significant insights and references for the identification of low-resolution images. A 360-panoramic system has been included by researchers into the process of target detection in underwater video collection and processing. In addition, application of binocular imaginative and prescient to generate image processing, combined with CNN, for fish identification. The recognition accuracies achieved were 87% and 83.2% for the respective methods. This inquiry pertains to the popularity of certain species. In [15] employed an advanced version of Convolutional Neural Network (CNN) to accurately identify live crabs in underwater environments, achieving a remarkable accuracy rate of 99.01% . In contrast, the researcher utilised a CNN model based on the ShrimpNet architecture to accurately recognise prawns, achieving a recognition accuracy of 95.48%. A comprehensive explanation of several models employed in image processing may be found in Table-3.

TABLE-3 Different image processing for fish counting

Author	Model/algorithms/technology	Environment	Data set	Accuracy/results	Models used
Fernandes, 2020	Linear regression and CNN	Lab	1653 artificial photos of Tilapia from the Nile	A (fish area): R2 = 0.96, MAPE = 11.35 A2: R2 = 0.95, MAPE = 12.35	Linear regression
Zhang, 2020	BPNN+PCA-CF	Lab	In the laboratory, 455 picture data sets were obtained	RMSE = 0.0137, R2 = 0.9021, MAE = 0.0104	LDA, KNN, SVR, DT
Zhang, 2020	CNN	Ocean	Ocean mariculture cage data collection "Deep Blue 1"	Pearson coefficient is 0.99, Accuracy is 95.06%	MCNN, CNN
Liu, 2018	CNN (Local count regression network)	Lab	537 pictures from 30 different sequences	RMSE = 16.48 MAE = 10.98	CNN, Regression network
Hernandez Ontiveros, 2018	LS-SVM	Lab	16 picture sequences	Average precision is 96.64%	SVM
França Albuquerqu, 2019	MV	Lab	There are 20 datasets of video images, with each dataset including 30 frames per second.	Pearson coefficient is 0.9996 Average accuracy is 97.4%	No
Le and Xu, 2017	MV	Lab	Video evidence collected within the lab	Average faultiness is less than 6%	No

3.2.2. Counting by video analysis

Counting objects in aquaculture with a single photograph is an inefficient method. Therefore, there is a need for a reliable and economical technique to accurately tally objects submerged in films. Visual surveillance presents itself as a promising technique for quantifying the number of objects, while efficiently circumventing the problem of duplicating the count of the same item. There is a utilisation of particle tracking velocimetry (PTV) technology to estimate the population of small and densely-packed fish in a tank, despite doing the experiment in a laboratory setting. The Kalman filter and the Hungarian approach in a densely populated setting to determine the central position of fish and estimate their number in consecutive frames, while considering the variability of their paths. The proposed method, however, has a substantial temporal complexity [16]. In their study, researcher employed a closed-loop methodology that integrates tracking and detecting techniques to address the issue of false positives in fish detection. These false positives arise due to similarities in the appearance and coloration of fish with those from previous records. This gadget utilised the visual data acquired by an underwater camera affixed to a remotely controlled vehicle (ROV). The researcher devised a tracking strategy primarily utilising the deformable multiple kernels monitoring technique and suggest-shift algorithm, which does not need training. This approach was inspired by the Deformable Part Model. The use of this technology surpassed conventional approaches in monitoring several fish in underwater motion photographs, resulting in a substantial reduction in computational burden [17]. The researcher introduced an innovative technique for monitoring and segmenting fish in stereo videos. This approach involves turning 2D items in photos into a 3D representation. Their monitoring system included a very complex convolutional neural network and a Kalman filter for 3D restoration, leading to improved understanding of badly distorted fish and increased overall monitoring efficiency. Machine learning excels at extracting functions and evaluating sample credibility and have employed a genetic algorithm to identify the Regions of Interest (ROIs) for fish, streamlining the assessment of fish abundance in a coral environment that is influenced by turbidity. Despite the notable efficacy of their approach, it encounters two consistently challenging issues. Initially, the accuracy of reputation tends to decline as the level of bio-fouling intensifies. Furthermore, when fish density increases, there is a clear and significant rise in the occurrence of false negatives [18].

3.3. Counting based on acoustic technology

The distance for underwater photography is restricted due to the moderate attenuation induced by the absorption and scattering of water. As the distance of capture increases, the photos get progressively blurred, and the quantity of shots taken decreases. In contrast, sound waves may propagate across water with minimal reduction in intensity. Consequently, auditory counting proves to be useful in instances when counting by sight is challenging.

3.3.1. Counting by hydroacoustic methods

The hydrophobic approach is widely employed due to its quantitative and non-invasive nature. Echo sounding is a technique that utilises the analysis of reflected sound waves to determine mass. Complex noises are produced by echo sounds when they interact with objects of different sizes. Hydroacoustic technology may be utilised to detect and enumerate fish in water, especially in arid and dry environments where eye observation is restricted.

The author assessed fish populations by measuring the intensity of the echo signal inside the surveyed region of an echosounder. However, this approach has constraints as it can solely identify acoustic waves when the fish's dimensions are adequately substantial and there exists a notable disparity between two species, rendering it less appropriate for identifying diminutive fish schools. The echo computation approach primarily use single-beam sonar. Dual-beam echo sounders and split beam sounders have been developed to provide images of comparable quality to those obtained by RGB cameras. Research was done to evaluate the main advantages and limitations of hydroacoustic techniques. Furthermore, there were apprehensions raised about the possible adverse impacts of sonar devices on marine organisms. [19].

3.3.2. Counting by acoustic methods

Dim and turbid conditions often impair underwater visibility, leading to subpar photo quality. Acoustic imaging is a new approach that may be used to gather information about the underwater environment specifically for the purpose of counting items. Sonar-based imaging is a well-established technique that uses sound waves to create images of things. These images may be analysed and processed to identify and locate the items. The Dual-frequency Identification Sonar (DIDSON) is a sonar system that use several beams and was developed by the Applied Physics Laboratory at the University of Washington. It is widely employed for capturing underwater sound pictures to identify fish species and estimate population sizes. The DIDSON system is capable of producing high-resolution images in shallow water and murky conditions, exhibiting image quality that is on par with colour cameras. A fixed DIDSON device was employed to continuously observe fishing trips and enumerate migratory fish in a small coastal estuary. An automated-assisted technique was employed to assess the abundance of migratory fish in the water. Nevertheless, the process of analysing DIDSON data in order to forecast fish populations is evidently laborious and requires a significant amount of time. In addition, the Adaptive Resolution Imaging Sonar (ARIS) captured high-quality images that were comparable to near-video quality when positioned at a fixed location. The author has addressed this issue.

The researcher used Adaptive Resolution Imaging Sonar (ARIS) in conjunction with DIDSON-based acoustic imaging to collect images of fish. The fish regions of interest (ROIs) were acquired via the use of area detection and watershed segmentation methods. Afterwards, a Support Vector Machine (SVM) classifier was used to precisely detect the presence of moving fish in the photos. The estimation of local abundance was conducted using an autoregressive time series model that integrated a zero-inflation Poisson distribution, yielding a counting accuracy of 94% [20].

4. Comparison of various fish counting methods

Precise enumeration is essential in the aquaculture sector for assessing stock levels and enhancing breeding protocols. An extensive literature research and survey were conducted to investigate the methods and technology employed in the enumeration of aquaculture items throughout the past several years. The paper examines the benefits and drawbacks of sensor-based, computer-vision-based, and acoustic-based counting methods. Significant improvements in the accuracy and generalisation capabilities of counting algorithms have been achieved through notable advancements in machine learning and deep learning in the domain of computer vision. Notwithstanding these progressions, sensor technology continues to be a feasible and pragmatic choice for fish enumeration. The simplicity of sensor installation and the affordability of sensor maintenance enhance its ongoing importance [21-30]. The various techniques for counting fish are detailed in Table-4.

TABLE-4 Different fish counting methods

Counting techniques		Advantages	Disadvantages	Application
Sensor based	Sensing	Swift response, uncomplicated execution	The presence of equipment may restrict the migration of fish and cause injury to them. Additionally, the potential impact of overlapping fish populations on the equipment is often underestimated.	Incorporated within the tallying system for quantifying decorative fish
Computer vision	Image Processing	Enhanced precision achieved by refining algorithm architecture and optimisation, without the need for intrusive procedures.	The necessary computational capacity of the equipment, the reduction in light intensity underwater, and the inability to count forever.	Quantification of animal population or abundance in underwater photographs using remotely operated vehicles (ROVs)
	Video analysis	Real-time and effective		
Acoustic based	Hydroacoustic methods	Swift and effective, impervious to water cloudiness or illumination	Discerning small and overlapping fish can be challenging.	Quantification of fish populations in aquatic environments such as lakes or rivers
	Acoustic imaging	Capable of capturing high-quality images in low-light and turbid aquatic environments.	It has low sensitivity and specificity for early lesions	

5. Conclusion

Aquaculture plays a crucial role in supporting the livelihoods of numerous individuals in India, with wide-ranging implications for several industries. Ensuring a balanced supply of fish is crucial for meeting consumer demand. India's freshwater aquaculture sector, responsible for 55% of the country's total fish output, positions India as the top global provider of seafood and local fish. The economic development of India is closely intertwined with the prosperity of aquaculture. As mentioned earlier, implementing advanced fish counting strategies enhances both the quality and quantity of aquaculture production while reducing personnel costs. This surge in productivity contributes to the elevation of India's GDP and facilitates the expansion of foreign exchange. The strategic application of contemporary technology, like as image processing and video analysis, in fish enumeration also enhances the effectiveness of aquaculture operations.

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