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MACHINE LEARNING IN FISHERIES SECTOR: A STUDY ON SMART AQUACULTURE SYSTEM IN INDIA

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Abstract
The use of artificial intelligence and automation in aquaculture to increase productivity and sustainability is a relatively new idea. Modern intelligent technology's widespread usage has benefited many sectors, including aquaculture, by greatly reducing labour requirements, improving aquaculture output, and having a negligible impact on the natural environment. Machine learning is a branch of artificial intelligence that employs pre-trained model algorithms to recognise and learn characteristics from the data it encounters. Water quality monitoring, farm management systems, turbidity sensors, pH metres, feeding control methods, a fish grader for assessing and controlling fish populations, and fish disease and health management are all examples of how machine learning has been applied in smart aquaculture. The research results in this article offer a synopsis of recent smart aquaculture and intelligent technology advancements. We analysed 75 studies from the last decade on the topic of machine learning's impact on smart aquaculture. The articles focus on the research process, the findings, and the most promising new technologies that could inform the field's future.
Key Words: Artificial Intelligence, Machine Learning, Fisheries

1. Introduction

The importance of the fishing and farming industries to the world's supply of healthy food has been highlighted in the last two decades. Global fisheries and aquaculture policy, management, innovation, and investment must undergo substantial shifts to better achieve this goal. A new record of 214 million tonnes was produced in 2020 from fisheries and aquaculture, an increase of 3% from the previous record-setting year of 2018. This includes 36 million tonnes of algae and 178 million tonnes of fish (213 million tonnes). Slow expansion is mostly attributable to falling catches of pelagic species, especially anchoveta, a decrease in China's catches, and the consequences of the COVID-19 pandemic in 2020. Despite a slowing annual growth rate, aquaculture has more than made up for the drop in fisheries in the past two years.

It was predicted that by 2025, the overall value of global catch fisheries production would be USD 141 billion, down 4.0% from the average of the prior three years, with 78.8 million tonnes coming from marine waters and 11.5 million tonnes coming from inland waterways. Once again, the anchovy is the most frequently caught marine fish, accounting for

85% of the total. Tuna, mollusc, shrimp, and lobster harvests all maintained or near record levels in 2020.

It is projected that global inland water catches will total 12.5 million tonnes in 2025, from 12.5 million tonnes in 2020. Nonetheless, this is still a record high, as more countries are now reporting their captures. The majority of the world's inland fisheries were harvested in Asia, with Africa coming in second. India's 1.8 million metric tonnes of inland fisheries production surpassed China's 1.6 million metric tonnes for the first time since the mid-1980s. The global aquaculture business reached a new high in 2020, producing a total of 122.6 MMT, including 87.5 MMT of aquatic animals worth USD 264.8 Billion and 35.1 MMT of algae for USD 16.5 Billion. There were a total of 68.1 million metric tonnes produced through marine and coastal aquaculture, with 54.4 million metric tonnes coming from inland water sources.

By 2020, it was 58.5 million people will be working in the primary agricultural industry, including jobs in fisheries and aquaculture. While the worldwide population of fishermen has decreased, the percentage of people working in aquaculture has remained relatively constant, at around 35%. Eighty-four percent of the world's fishermen and aquaculturists lived in Asia in 2020. Twenty-one percent of workers in the primary industry were female in 2020; however, only fifteen percent of full-time workers were female in aquaculture and fisheries. When looking at statistics specifically for the processing industry, however, women made up slightly more than half of full-time workers and 71% of part-time workers.

Conventional aquaculture entails a number of technical procedures, including water purification, seed selection, food preparation, and care for the young throughout their development. The process of water quality management in the aquaculture system is just one of the many obstacles people face on a daily basis. This process takes a long time, and in cases when the water quality in ponds or tanks suddenly declines, it may not be able to clean the water in time. Another scenario where early detection of illness is impossible and treatment is administered only after the fish have died or surfaced is the rearing of fish in ponds. The quality of the water in the pond might be negatively impacted by the food that has been left over, and it is impossible to predict how much food is now in the pond. Counting fish prior to sale is a time-consuming and labor-intensive process since each individual fish must be counted. The aforementioned issues have a negative impact on aquaculture's bottom line. Hence, the purpose of smart aquaculture is to employ intelligent ways of production that address issues plaguing conventional aquaculture.

The term "smart aquaculture" refers to the practise of cultivating aquatic organisms in a setting where environmental parameters affecting the water they are exposed to are constantly monitored and decisions are made automatically based on the data collected. Aquaculture can be an extremely effective means of production if done correctly. Remote monitoring and control, as well as automation, are made possible by the use of technologies like the Internet of Things (IoT), big data, artificial intelligence (AI), 5G, the cloud, and robotics. A robot, on the other hand, might be responsible for monitoring the facilities, equipment, and tools used in smart aquaculture to ensure they are operating at peak efficiency (Kassem n.d.).

Many sensors (for things like temperature, dissolved oxygen, humidity, light, and pH) in an aquaculture system must send their readings to a hub, where they can be analysed and decisions made before finally being saved in the cloud for future reference. Lastly, all of the machinery employed in the process's execution phase needs to receive feedback from the assessments and decisions made earlier.

For instance, in aquaculture, there has been an uptick in the usage of technology like artificial intelligence and the Internet of Things to deal with some of the difficulties that have long plagued the industry (Imai n.d.). They are used for a wide variety of purposes, including water quality monitoring, and are implemented in a wide range of culture systems, including cages, ponds, hatcheries, and breeding facilities (Hamid n.d.); Keeping an eye on things in the cages, pond, and hatchery; figuring out how much food to give cultured species and when to give it to them; reducing the amount of time between feed deliveries for cultured systems; labour savings through computerization of cultural systems (Rashid n.d.).

2. Concepts of Machine Learning

The convergence of these three technologies has opened up novel avenues for studying, quantifying, and making sense of data-intensive processes. Machine learning (ML) is an approach to computing that aims to reduce the necessity of programmed instructions. The field of machine learning known as "deep learning" applies artificial neural networks to the task of simulating natural human behaviour. Deep learning (DL) is a subset of machine learning with promising uses in several AI-related contexts (AI) (Deng & Yu 2014 n.d.).

The fundamental difficulty of representation learning is addressed by deep learning by allowing computers to construct complex concepts from smaller notions. Raw sensory input data, such a picture represented as a series of pixels, is challenging for computers to immediately grasp the meaning contained within. The functions used to convert a grid of pixels into a 3D model are quite intricate. The use of direct programming to acquire or assess such a mapping appears to be unfeasible (Bronstein et al. 2017) n.d.). In order to address this issue, DL breaks down the complicated mapping into a hierarchy of smaller mappings. For instance, a picture is fed into the first visible layer, and then the picture is fed into a series of hidden layers that extract progressively abstract elements. The first layer can tell if a given pixel is an edge by comparing its brightness to that of neighbouring pixels. In the next concealed layer, it looks for groups of edges that may be deduced to represent angles and expanded shapes (Sritha Zith Dey Babu n.d.). The third concealed layer is then able to locate the exact collection of contours and corners that represent the entirety of a given section of an item. The numerous visual features can at last be pegged down (Goodfellow et al. 2016 n.d.).

Machine learning's major goal is to boost the effectiveness of computers by creating mathematical models from data and unique techniques. These days, aquaculture researchers use a wide variety of models, including decision trees (DT), naive Bayes (NB), support vector machines (SVM), artificial neural networks (ANN), K-nearest neighbour (KNN), deep learning (DL), and ensemble learning (Ma n.d.).

Together with unsupervised learning, semi-supervised learning, and reinforcement learning, supervisory learning is one of the most often used architectures in machine learning. Classification and regression are two common supervised learning applications in machine learning, where the data is utilised as a sample after training by a model with the same target values. Aquaculture is one of the newest fields to profit from the theory and advantages of machine learning. In a wide variety of contexts, including fish species identification, feeding behaviour, group behaviour, deviant behaviour, univariate prediction, and multivariate prediction, these approaches have consistently demonstrated excellent levels of accuracy (Barzegar n.d.).

Here, we'll assess the current state of smart aquaculture machine learning applications. The next sections will outline the reasoning for this assessment. Understanding Smart Aquaculture, Using Machine Learning, and Applying Machine Learning to Smart Aquaculture. An overview of sophisticated aquaculture monitoring and sensing systems is shown in the accompanying diagram.

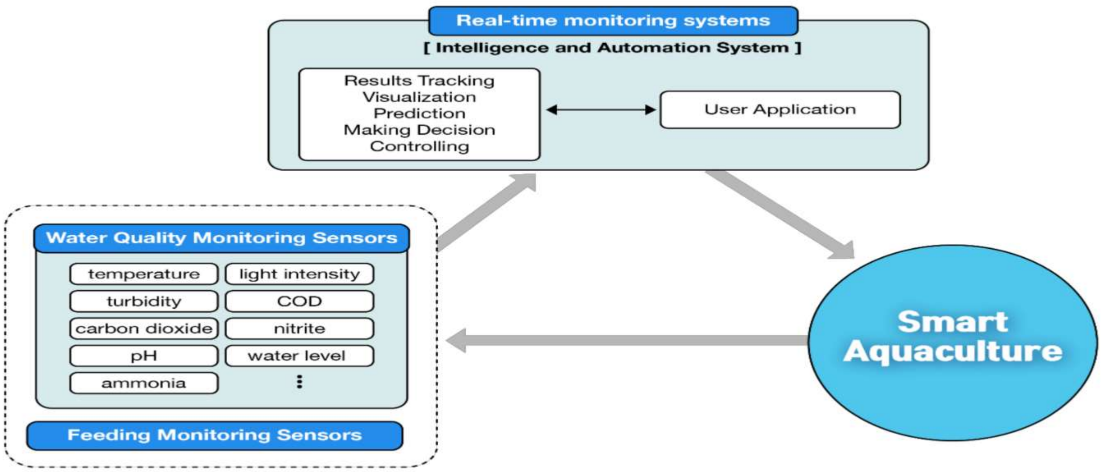


Fig: Introduction to Intelligent Aquaculture Monitoring Systems (Vo et al. 2021) .

3. Review of Literature

Aquaculture uses deep learning (DL) due to its rapid development. DL expands smart fish farming data processing possibilities and problems. In aquaculture, we use DL to classify live fish, analyse their behaviour and feeding habits, estimate their size or biomass, and predict water quality. DL-based smart fish farming data, algorithms, and performance are assessed. DL's automatic feature extraction was particularly beneficial. DL requires a lot of labelled data for training, which has hindered its adoption in aquaculture. DL advances aquaculture data analysis. Our mission is to help scientists and farmers comprehend cutting-edge aquaculture technology, which will promote novel fish farming methods (Agossou and Toshiro 2021).

Aquaculture output grows worldwide. Aquaculture requires human expertise. AI has enabled widespread automation in several production areas. This work investigates real-time fish detection using deep learning as a first step towards smart farming. Deep learning-based object detection models are evaluated on real-world fish data and contrasted and analysed (Shin, Choi, and Suk Choi 2020).

Open-water aquaculture underwater fish cages must reduce labour and feeding costs. This study introduces the Smart Aquaculture System, which uses automated feeding, continuous cage surveillance, and optimised feeding timing and quantity to reduce aquaculture labour costs while maintaining high yields. The Remote Feeding System incorporates a smartphone and a cage-mounted feeding mechanism. Our in-field tests—including some underwater ensured that everything was working properly (Imai, Arai, and Kobayashi 2019).

Aquaculture is the practise of cultivating fish, crabs, mollusks, and other aquatic animals for human consumption. The demand for fish oil, marine collagen, seaweed, algae, and others is expanding the industry. The cultivation of aquatic organisms is difficult and calls for careful management of numerous variables. Effective algorithms and technological advancements are prerequisites for intelligent aquaculture. Real-time environmental monitoring and rapid risk mitigation are made possible using sensing and machine learning approaches. Sensors (physical, biological, optical), automation, and automated decision-making are all summed up in this chapter (Sharma and Kumar 2021).

Intelligent fish farming methods that show how difficult scientific and technological processes can be simplified for widespread use in the seafood industry. In this study, we will examine how AI can be applied to the aquaculture industry. At a fish hatchery, AI can help with critical jobs since it uses an Artificial Neural Network to mimic the capabilities of the human brain. In order for fish in captivity to thrive, grow, and perform any other life process, water quality is crucial. Systems based on artificial intelligence can be developed to regulate key water quality indicators like salinity, dissolved oxygen, pH, and temperature. YSI's multi-parameter water quality metres are used in this system-level method, together with a software application running on an application server. The YSI device's parameter values are read by the software, which then verifies that they fall within the optimal range. In any other case, an alert system would sound, allowing the people in charge of the hatchery to take whatever necessary corrective measures are necessary right away. As a result, the hatchery's life-supporting system may function more accurately, efficiently, and affordably. Although this system's evolution has been complex, the resulting application is straightforward enough to be managed by a well-coordinated fish farming community. Given the novelty of the method of aquaculture management introduced in this study, it was thought necessary to provide some context for the challenges at hand (Mustafa 2016).

The system's design calls for data from the farmed field to be sent to the Ocean Cloud data platform, where it will be analysed using big data techniques and then applied to the cage culture field. This management system is successfully used in cage culture, integrating AI and IoT technology. It explains how the system blends A.I and IoT to develop a practical framework that can continuously capture information about the health status of fish, the survival rate of fish, and the feed residuals using underwater biological analysis photographs as examples. The findings will help aquaculture owners and managers cut down on wasteful feed residual, track fish growth, and boost fish survival rates, all while enhancing feed conversion efficiency (Chang et al. 2021).

Agriculture would not be what it is today without aquaculture. Farm disasters on a massive scale occurred because people trusted their own abilities. The quality of water used in aquaculture is affected by a number of external variables. One of the most important aspects of aquaculture is the upkeep of a high-quality aquatic environment suitable for the growth of the animals. Aquaculture is becoming more intelligent and informatized as a result of scientific and technological advancements. The monitoring of fish behaviour and the surrounding ecosystem may now be done in real time thanks to smart aquaculture. Also, the physical and chemical aspects of aquaculture can be tracked, predicted, warned about, and managed to reduce exposure to danger. Twenty years of study are summarised in this work, with a focus on four primary areas: the collection and pre-processing of data on water quality indicators; their prediction; the recognition of fish morphological and behavioural attributes; and the mechanism linking these qualities to water quality. The benefits and drawbacks of various smart aquaculture research methodologies, algorithm models, and study plans are outlined.

Future studies on the interactive mechanism between water quality parameters and fish behaviour can refer to this report as a starting point for their own investigation. The work may also contribute to the sustainable growth of aquaculture (Hu et al. 2020).

The proliferation of internet-enabled gadgets has cleared the way for the development of smarter ecosystems in many fields. Most notably, the incorporation of internet-connected devices with technologies like big data, AI, block-chain, etc. has led to greater efficiency and productivity. As a result, fish farm operators have started implementing smart fisheries technologies. Smart fisheries, for all their technological achievements, are susceptible to cyber-attacks that might have disastrous ecological and financial consequences. In this study, we explain the architecture of a smart fisheries ecosystem, which details the many ways in which smart devices communicate with one another through the internet. We build an ontology for smart fisheries using this framework, and use Attribute Based Access Control (ABAC) to enable request-based authorization to the fishery's resources. In addition, we talk about the factors that go into access control decisions in various smart fisheries ecosystem use cases. Also, we expand on a few artificial intelligence (AI) applications that could help the smart fisheries ecosystem (Chukkapalli et al. 2021).

Traditional fish farming is plagued by several problems, such as water pollution, temperature imbalances, feed, space, cost, labour, and so on. By recycling waste feed into microbial protein, biofloc technology is able to revolutionise aquaculture from traditional to cutting edge. The study's goal is to find an Internet of Things-based answer that can boost aquaculture output and efficiency. The article described a system that monitors its environment with the help of sensors and then utilises a machine learning model to make judgements and send alerts based on those decisions. Validation and a positive outcome have been achieved after implementing and testing the suggested system (Rashid et al. 2021).

Both aquaculture and the Internet of Things have grown rapidly in recent years, but their junction is just getting started. Due to its intricacy, water monitoring is often disregarded by fish farmers, despite its centrality to the industry. Our efforts to deliver approachable IoT solutions for fish farming are expected to usher in a new era of connected, responsible, and efficient aquaculture. Aquaculture IoT must be cost-effective, time-efficient, trustworthy, user-friendly, and easy to implement. Also, by learning from and acting upon critical information gathered via the Internet of Things, artificial intelligence can facilitate the delivery of novel services that cater to the specific needs of the aquaculture industry (e.g be efficient but green). Here, we present the results of the European research projects that laid the groundwork for the future generation of aquaculture (Dupont, Cousin, and Dupont 2018).

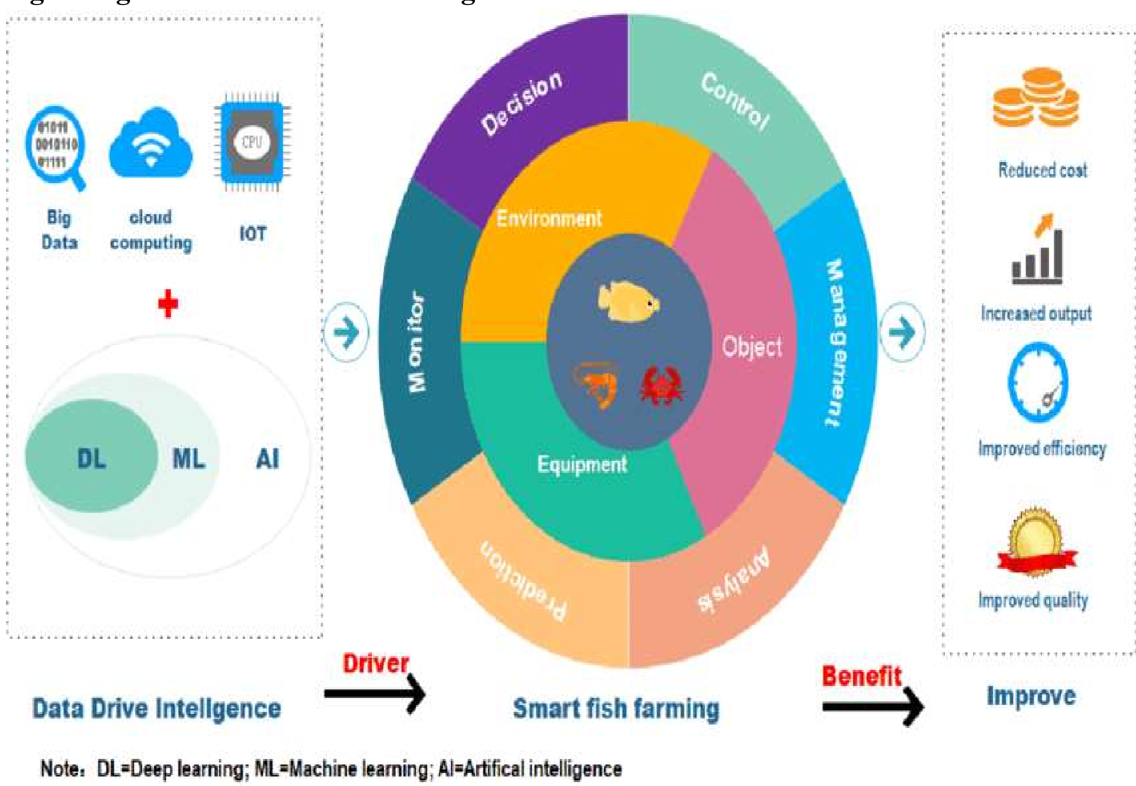
With the help of DL technology, aquaculture has grown at a quick pace. When applying DL to the processing of data from smart fish farms, there are both new opportunities and new obstacles to consider. Classification of species, behaviour analysis, diet selection, size/biomass calculation, and water quality forecasts are only some of the aquaculture applications of DL explored here. The experiment's data, methods, and results from a "smart fish farming" trial powered by deep learning. The automatic extraction of qualities is an area where DL has been found to shine. A major roadblock to the widespread use of DL in aquaculture has been the requirement for massive amounts of labelled data for training purposes. To this day, DL remains the gold standard for addressing complex data problems in the aquaculture sector. We share LD aquaculture expertise to promote ecologically sound, high-quality fish farming (Yang et al. 2021).

4. Smart Aqua-culture:

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

Using cutting-edge information and communication technologies such as the Internet of Things, big data, cloud computing, artificial intelligence, and others, "smart fish farming" enables the most efficient use of available resources and promotes the sustainable expansion of aquaculture. Meanwhile, a novel approach to fishery production has emerged, with an emphasis on real-time data collecting, quantitative decision making, intelligent control, precise investment, and personalised service (Xinting Yang1 n.d.).

Fig-1: Big data in smart fish farming



Information is the key to data-driven fish farming. Scientific decision-making will be made possible by the acquisition of data and its advanced analysis. The mountain of data generated by smart fish farming presents difficulties, such as variations in data quality, formats, and sources. Many resources provide information on equipment, fish, environment, breeding method, and human resources. There are several subtypes of data, including text documents, photographs, and audio recordings. Species, production techniques, and stages further complicate the data. Working with large amounts of nonlinear, high-dimensional data can be challenging.

These days, data and AI play a crucial role in aquaculture operations. Data-driven intelligence techniques, such as artificial intelligence and big data, are beginning to translate these datasets into actionable insights for smart fish farming, as depicted in the graphic above

(Bradley et al. 2019 n.d.). The next major improvement in fishing data systems will come about as a result of artificial intelligence, and more especially, machine learning and computer vision. Support vector machines, artificial neural networks, decision trees, and principal component analysis are all examples of classic machine learning techniques that have found success in a variety of contexts (Wang et al. 2018). Yet, it remains difficult to ascertain which characteristics are most appropriate for a specific task, and standard machine learning algorithms rely significantly on features manually designed by human engineers (Min et al. 2017 n.d.).

As well as improving the breeding, nursery, and grow-out phases of cultured species, smart aquaculture has the potential to improve the other processing steps involved, such as the preparation of cultured water resources, the management of water quality, the preparation of feed, the feeding process, classification, grading, counting, and washing the cultured systems. Sustainable aquaculture development aims to enhance production to meet global demand without compromising environmental standards.

Water Quality Monitoring in Smart Aquaculture

The success and efficiency of aquaculture depends on the condition of the water used in the industry. Many water quality indicators have been studied because of their impact on the growth and survival of cultured organisms. These factors include temperature, turbidity, carbon dioxide, pH, alkalinity, ammonia, nitrite, and nitrate. The most influential factors are heat, oxygen saturation, and acidity. One sector that has adopted IoT is aquaculture. The development of smart, linked devices that can track changes in water quality in real time has sparked a new trend towards aquaculture that doesn't drain the environment. In the workplace, this is a huge improvement for those who work in aquaculture.

The levels of an IoT aquaculture system are depicted in the following graphic, from bottom to top: physical, monitoring, virtual, and connection protocol. The goal of the smart farming/intelligent aquaculture movement is to maximise output per worker while decreasing expenses. It's possible that fish infections can be detected using IoT-based technologies, which could then be used to avert any output losses. Although AI tools have contributed to the growth of smart and precise aquaculture, there are still many obstacles to overcome before completely automated systems can be used (Li and Li 2020).

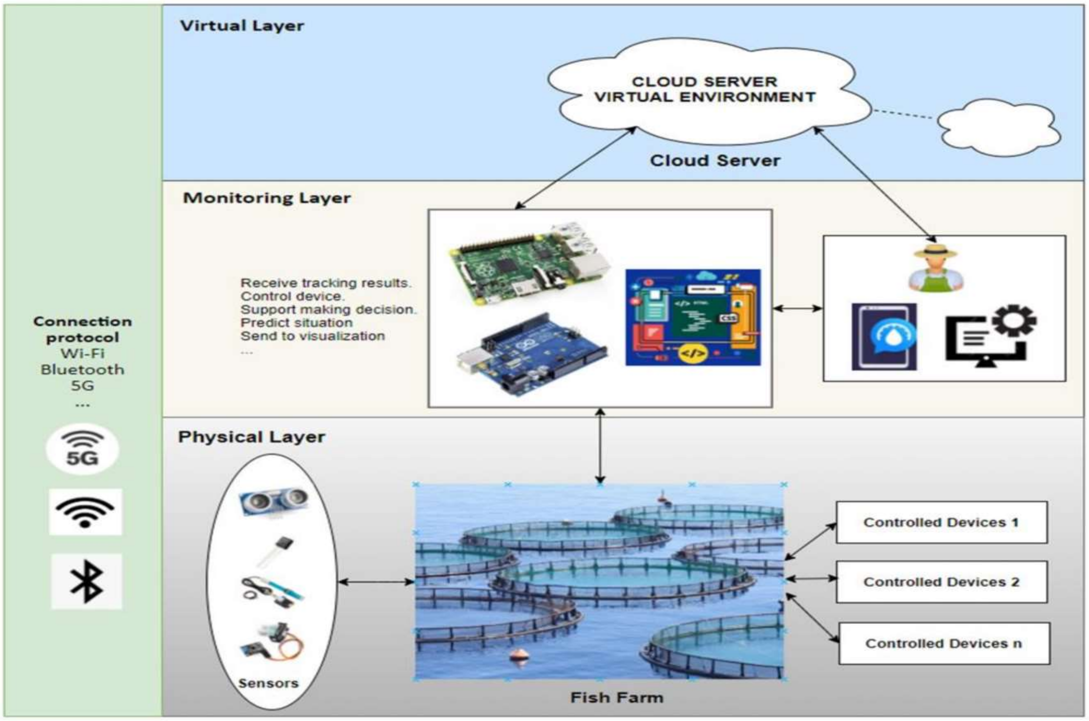


Fig-2: Internet of Things (IoT) Aquaculture System (Chiu et al. 2022).

Managing workers in the aquaculture business is risky because to the fact that fish farming still requires some degree of human observation, analysis, and judgement due to the specific nature of aquaculture and its outputs. Yet, a great deal of sophisticated equipment, including the technologies outlined above, is in charge of monitoring the conditions in fish farms. Fish farms are getting increasingly mechanised, and production robotics are just one example of this. They have a variety of applications in fish farming, including stock monitoring, fish size measurement, and behaviour modification. Also, proof of the sustainability of the IoT aquaculture system requires a brand new generation of sensors that are both extremely dependable and broadly adaptable (Li and Li 2020).

Smart aquaculture farm management system using IoT and AI-based

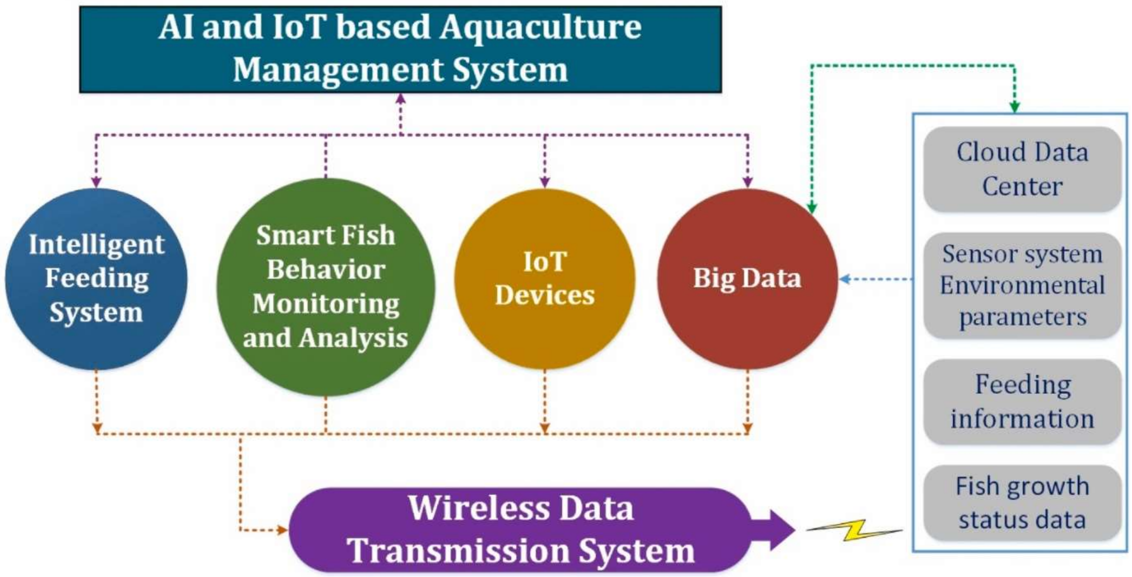


Fig-3: Flow chart of system operations.

Automation solutions like water quality monitoring and regulating systems and smart fish management systems are needed to reduce aquaculture facility staff. The AI & IoT system was developed using a system concept for intelligent aquaculture management. Internet of Things-based fish pond system architecture. The proposed smart California Bass fish pond has a controller Arduino Mega2560 with an integrated Wi-Fi module, a heater, limit switch, water pump, agitator, wind proofing device, smart feeding device, and IPCAM for continuous monitoring, as well as sensors for pH, temperature, dissolved oxygen, and turbidity. These sensors measure many parameters and send their readings to a cloud server through Wi-Fi for processing. The collected data is forwarded to the server system for AI and big data processing to estimate the features' productivity impact. Remotely monitor and control the system with a smart-phone app (Chiu et al. 2022).

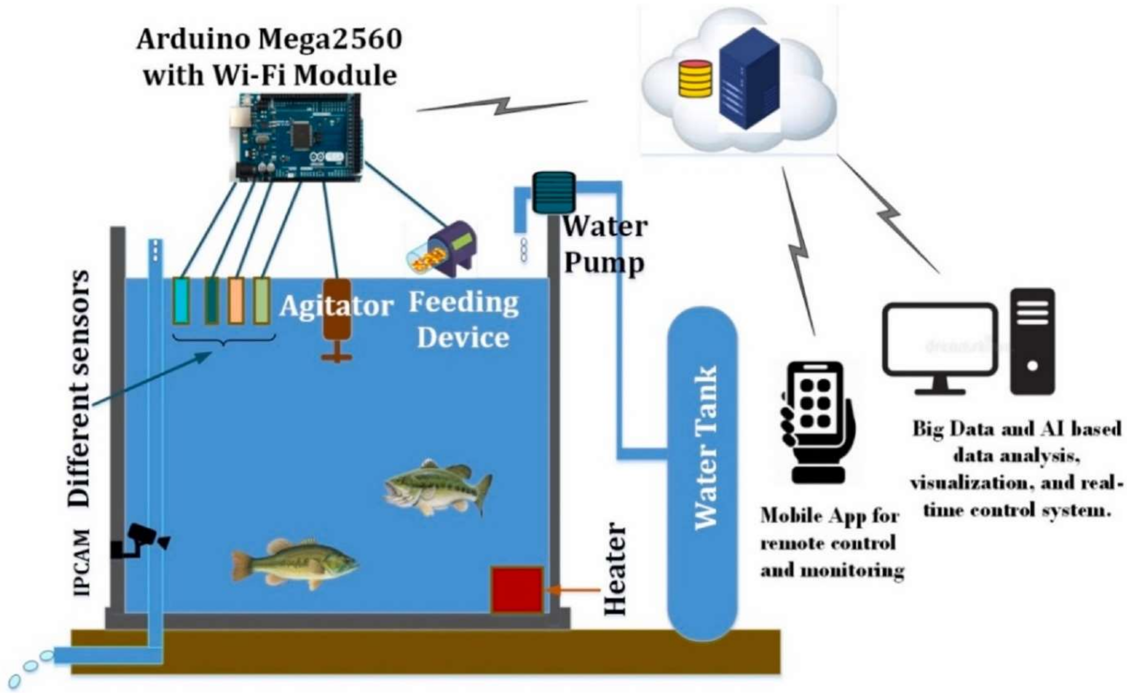


Fig-4: Feeding device

a C.W. and C.C.W. motor-powered wind-proofing device reduces heat convection caused by cold winds. The wind proofing device and heater activate when the thermal sensor detects low water temperatures. As shown in the Fig. the pond's internal agitator starts when the DO sensor detects dissolved oxygen below the set point. The pump activates if ph or turbidity exceeds your limits. Figure 3 shows the fish pond water quality management flow diagram. Finally, an IP CAM will be deployed underwater to verify baiting conditions for water quality and track aquatic creature development for intelligent feeding. (Chiu et al. 2022).

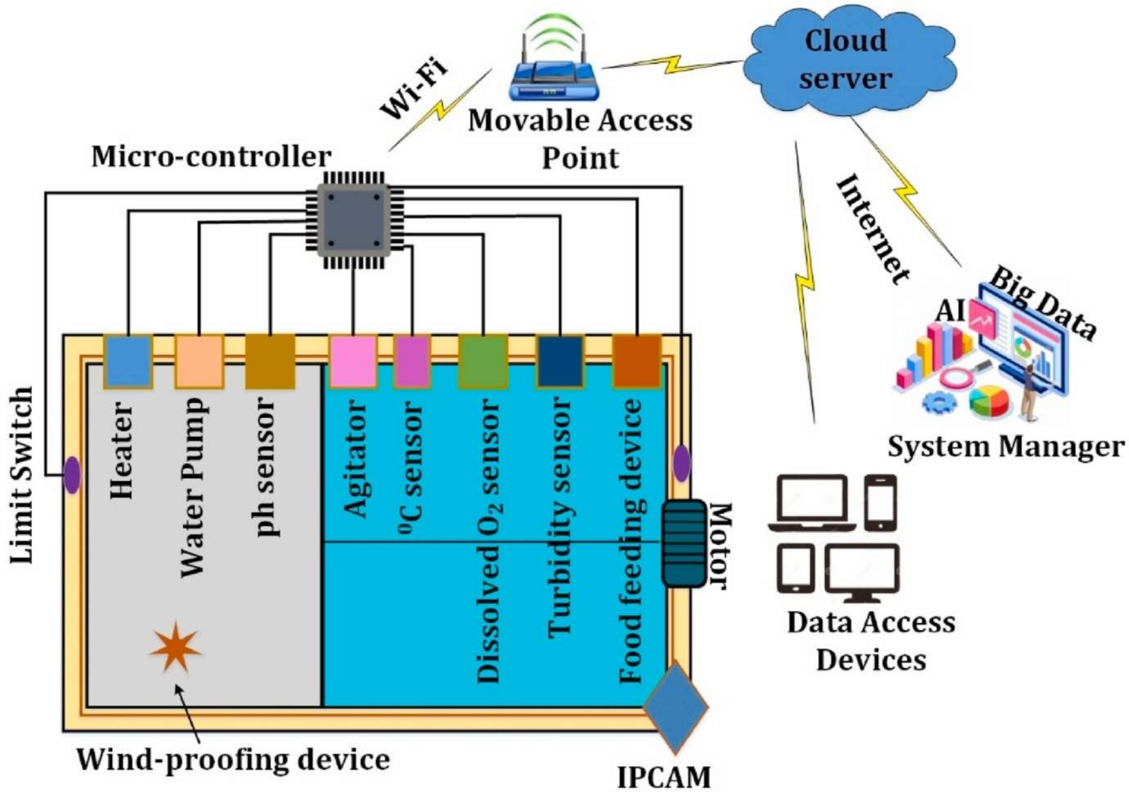
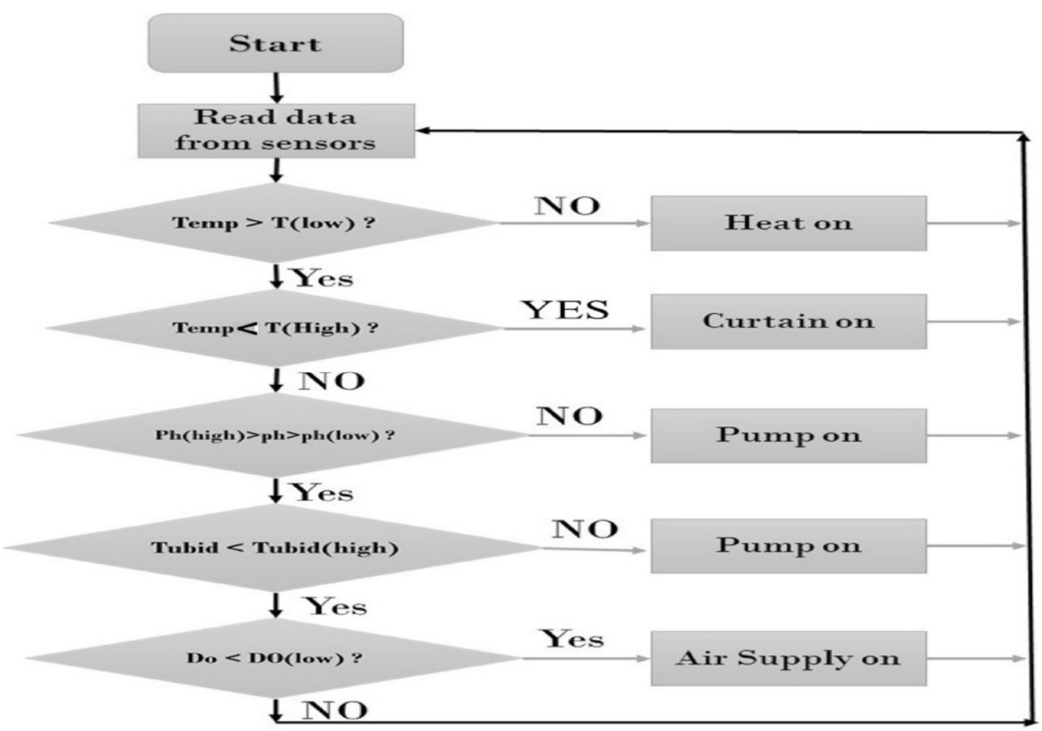


Fig-4: A fish pond equipped with automatic control of multiple sensors, multiple actuators, and IPCAM.



The algorithm of the water quality controlling process for the fish pond (Chiu et al. 2022).

Arduino Uno: The Arduino platform consists of an open-source hardware, software, and user community that collaborates to produce single-board microcontrollers and related kits. The use of its products is regulated under the LGPL or the GPL (GPL). There are a great deal of microprocessors and controllers on Arduino boards. Connect shields and breadboards with digital and analogue I/O pins. Boards are able to talk to and take orders from computers thanks to serial connectivity, such as USB on some versions. C and C++ can be run on microcontrollers. Complementing Arduino's compiler tool chains is the Processing-based IDE (Manual).

Node MCU: Node MCU is an inexpensive open-source Internet of Things platform. Initially, we used ESP-12 module and ESP8266 firmware. Then came support for the ESP32, a 32-bit Microcontroller. Board layouts for the prototype versions of the Node MCU firmware are freely available. Node MCU is an acronym that combines "node" with "microcontroller" (micro-controller unit). Firmware on node MCUs, as opposed to development kits, is what is actually being sold. Open source hardware and software are used in the firmware and prototyping boards. The firmware was written in Lua. The firmware was built using the eLua open-source project and the Espressif Non-OS SDK for ESP8266. There are many open source projects out there, including Lua-cjson and SPIFFS. Given the constraints of the available hardware, users are forced to "cherry-pick" modules for custom firmware. The 32-bit ESP32 can be used with custom firmware. New ESP32 functionality has been added. modified software. Addition of ESP32 support was implemented.

pH Meter: Any microcontroller can be connected to a pH sensor module, which consists of a pH probe and signal conditioning board that generate a proportional output based on the pH value. All of the sensors needed to measure pH are included in a single electrode that measures pH. However, measuring electrodes made of glass are quite delicate. Sensing devices once made of fragile glass have been replaced by solid-state alternatives. Signal preamplifiers set the stage for amplification. It takes the signal from the pH electrode, which has a high impedance, and transforms it into a form that can be read by an analyzer or transmitter. The signal is stabilised and amplified by the preamplifier, which makes it more robust against background noise. pH and ORP sensors detect the acidity of a liquid. On the pH scale, zero indicates complete acidity, whereas 14 represents complete basicity. A solution's ability to gain or lose electrons can be measured with an Oxidation Reduction Potential (ORP) probe, and the resulting voltage can be used to calculate pH. Image 4. Readings from the pH metre are sent in analogue form to Arduino. It's put to good use by us. Water with a pH of 0 is considered severely acidic, and so on up to 5. A higher voltage is accompanied by a lower pH, and bases do just that. In the simplest situation, voltage can approach 5. The pH scale can be calculated by multiplying the voltage by 2.8.

Turbidity Sensor: Turbidity Sensors can analyse freshwater and saltwater samples (Nephelometric Turbidity Units, the standard unit used by most water collection agencies and organizations). Its small size and simple setup make it easy to use at the gathering site. It also studies precipitate formation and algal and yeast populations in chemistry and biology labs. The Turbidity Sensor includes a high-quality glass cuvette for water sampling and a Hach StablCal 100 NTU standard for rapid calibration. The turbidity sensor accurately detects water quality using turbidity. To find suspended particles in water, it analyses light transmittance and scattering rate, which vary with TSS. TTS increases liquid turbidity.

Feeding control methods based on computer vision: Computer vision technology has been widely implemented in the aquaculture industry. Counting, measuring, determining gender, evaluating quality, identifying species and stock, and monitoring animal behaviour all benefit from the usage of these technology. Fish behaviour, feed consumption, and biomass are all interconnected and therefore must be considered when designing an intelligent aquaculture feeding system. Feeding behaviour analysis and feed detection, both of which rely heavily on computer vision technologies, are the sources of this information (Zion (2012) n.d.).

Feeding control methods based on acoustic technology: When compared to other methods for detecting and identifying small things submerged in water, acoustic waves are preferable because of their extensive range and minimal propagation loss in water (Taviti Naidu Gongada & Kiran Kumar Seepana n.d.). Stopping feeding can be done either by counting the number of fish or by using an audio sensor to observe their behaviour. Data collecting methods such as passive acoustics, sonar imaging, acoustic training, and bio-telemetry are all examples of this (Polonschii C n.d.).

Bio-telemetry: The animal-tracking technique known as bio-telemetry has proven useful in the aquaculture industry for both fish breeding and the detection of fish behaviour in real time, therefore giving the signals necessary for the creation of automated monitoring and feeding systems (Chris et al. 2009 n.d.). In the past, fish movement and position were measured by delivering a basic sound pulse signal using analogue electrical equipment and acoustic signal systems. Recent advances in embedded microcontroller and sensor technology allow for increasingly sophisticated telemetry transmitters that can be used to track fish and capture data about their habitat (Cooke et al. 2004a n.d.).

Automatic fish measuring system: Umitron's unique product uses AI and IoT technology to autonomously monitor fish size in aquaculture installations using a portable camera and mobile app. A good farm requires knowing how your fish are doing at each stage. Conventional fish growth procedures require frequent samples from a sufficient number of fish, which is time-consuming for farmers and stressful for the fish.

Umitron Lens automatically measures fish size in the cages using tiny stereo cameras and AI, and it syncs with the internet so that data may be stored in the cloud. The Japanese company claims that by automating the process of monitoring fish growth, farmers may save time, improve the efficiency of their business, and earn more money..

Umitron, a Japanese company, has been working on this since 2018 with the goals of providing a better service to farmers, collecting important data from measurement activities, and enhancing the precision with which sizes are estimated. The company developed a novel algorithm to enhance the precision with which fish bodies can be measured, and it employs compact stereo cameras to facilitate ease of use. Using Umitron's high-resolution ocean data service (Umitron pulse), smart auto-feeder (Umitron cell), and fish appetite analysis system (Umitron FAI), we can develop a more environmentally friendly aquaculture system (bream, 2020).

FISH GRADER FOR MEASUREMENT AND CONTROL:

The thickness of the fish is used by the VAKI Grader to separate different sizes of live fish, smolt, juveniles, and fry. The grader features 16 rotating boxes arranged in a hexadecagon. The opening in the bottom of the box is automatically widened as the box travels over an outlet, achieving the desired grading gap size. Adjustable grading gaps range from completely closed to a maximum width of 50mm. Thicker fish are more valuable. A single fish inlet complements the grader's four regular exits. Getting to know the mean and standard deviation of the original group is a great way to keep track of the quality of the graders. Simple and quick weight samples can be used to determine where grading gaps will open and how many fish will fall into each tier. Taking a sample of fish from each size category while the grader is operating allows for accurate measurements of mass, width, and length to be made. The next step is to evaluate the outcomes in light of the gap parameters and the previous weight calculations (https://pentairaes.com/media/requestforquote/fish-grader/docs/gradermanual2015eng.pdf).

Fig-5: Fish Disease and Health Management

A Smart Device for Monitoring Fish Health and Welfare

Miniaturized monitoring equipment, dubbed AE-FishBIT, has been developed to track the health of individual farmed fish without harming them. When compared to other available devices, this one stands out due to the fact that it measures both physical activity and respiratory frequency at once. Aquaculture farmers and other end users will find AE-FishBIT useful for tracking fish behaviour during selective breeding and when making fine-tuned adjustments to their aquarium's environmental settings.

A little device called AEFishBIT was developed to keep tabs on each farmed fish without harming them. Miniature tri-axial accelerometer for recording and processing data, AEFishBIT weighs less than a gramme and can be reprogrammed. Attached to the fish's operculum from the outside, the prototype charts accelerations along the x and y axes to track movement and respiration is tracked along the z axis to get a sense of the animal's heart rate. Both European sea bass and gilthead sea bream have been used to test and verify the device's effectiveness. Cultured salmon have also shown encouraging outcomes in preliminary studies. Device tagging did not appear to have any unfavourable effects based on visual observations of tissue damage, eating behaviour, or circulating levels of stress indicators. There is currently no other non-invasive tagging technology available that can assess both physical activity and breathing frequency at the same time, as far as the researchers are aware. AEFishBIT measures have been linked to either improved performance or variations in stress and disease resistance in field studies involving free-swimming fish subjected to a wide range of biotic and abiotic variables.

Biosensors for evaluating fish health

Biosensors are currently being actively researched and developed to analyse the functionalities of live creatures with electronic technology. Electronics have come a long way, and now we can monitor and detect certain compounds even in an extremely complicated setting. Enzymes and antibodies, two molecular components of biological processes, are utilised by biosensors in order to detect certain compounds. Biocatalysts can be used as sorting mechanisms because their reactions with substrates result in detectable shifts in physical quantities like current, resistance, and temperature as byproducts of the production and consumption of chemical species (Windmiller and Wang 2013 n.d.). By detecting these minute changes utilising signal conversion elements like electrodes and optical devices, biosensors can quickly and easily quantify targeted molecules. The development of biosensors to assess fish health is underway because of their great sensitivity and specificity (Grieshaber et al. 2008 n.d.).

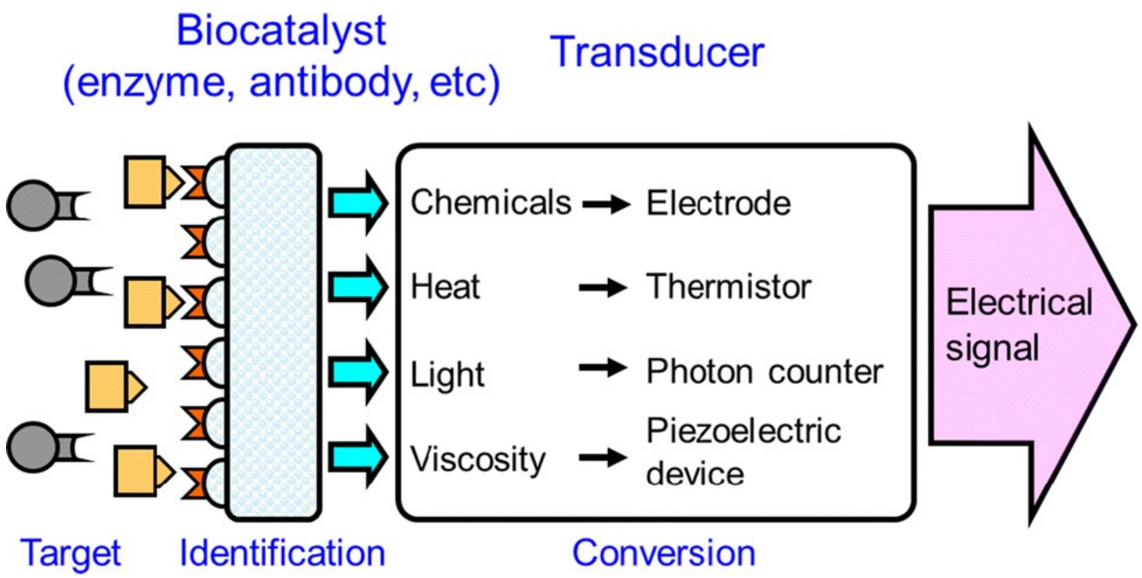


Fig-6: Principles of a biosensor.

5. Conclusions:

Intelligent aquaculture has grown quickly thanks to automation and precision. While the aquaculture industry is rapidly embracing AI, fully automated solutions are still a work in progress. Loss of human management in fish farming could impair observation, processing of data, and choice making. Aquaculture output has increased automatically due to the proliferation of machine learning and computer vision applications. Photos and algorithms can do the work far more quickly and accurately than people can. Because of the high cost and limited use of machine learning and computer vision, these technologies are best deployed on big farms that focus on commercially valuable species.

In this paper, we focus on the use of AI in smart aquaculture, with particular attention paid to machine learning and vision. Algorithms and machine vision for machine learning were explored by researchers and aquaculture producers. Counting fish, identifying species, monitoring feed, and evaluating water quality are just some of the common applications. In the near future, more machine learning and computer vision applications will be made available for use in smart aquaculture, which covers both on- and offshore aquaculture systems. Aquaculture relies on the utilisation of offshore areas, such as cages, to monitor fish health, prevent escapes, and regulate stocking density, fish size, and food distribution using machine learning and computer vision. Knowing how to spot a sick fish or a faulty cage net is essential. Aquaculture production cycles are often completed entirely by hand by farmers. For example, sick fish will swim to the surface to die, or else a human will need to dive down to check on them. As such, an underwater camera with built-in AI/vision capabilities would be incredibly useful. This device has the potential to serve as a model system for the future of offshore cage culture due to its ability to monitor fish health and to control the cage's environment in terms of its weight and the size of its inhabitants.

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