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Application Of Deep Learning (Ai) In Marine Fisheries Resource Management

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Abstract

Deep learning is defined as "the future built from fragments of the past." These are applications that, with use, provide new solutions. Artificial intelligence has been applied in a wide range of fields, from agriculture to complete industry automation. AI can even be used to prevent the extinction of aquatic life forms. AI supports global fishing activity monitoring and the sustainability of open sea fisheries. AI is crucial in the fight against IUU fishing. Artificial intelligence in image identification has rapidly advanced in recent years, as seen by the wide range of uses it has in contemporary culture. This has created new prospects for improving coral reef monitoring skills. Using a global coral reef monitoring dataset, we assessed the effectiveness of deep-learning convolutional neural networks for automated picture analysis. The study highlights the benefits of automated image analysis for coral reef monitoring in terms of cost and benefit as well as error and repeatability of benthic abundance estimates.

Keywords: Deep learning, Application, Marine fisheries, Management

1. Introduction

The world economy's aquaculture and fishing sectors alone would create 122.6 million tonnes of aquatic goods worth USD 281.5 billion in 2020. With almost 91.6% of the global aquaculture production, Asia continues to lead the way. The output of aquatic animals is expected to increase by 14% by 2030 (Lim, 2022). Deep learning is computer programs that simulate human-like reasoning in a computerised system. Currently, IOT connects around 50 billion electronic gadgets, many of which are AI-powered. Artificial intelligence is now being applied to the agriculture and fishing industries. By monitoring worldwide fishing activities using a combination of satellite data, AI in fisheries aids not only in farm management but also in open sea fishing (Jothiswaran *et al., 2020*). AI is sometimes referred to as "the future made from the pieces of the past." By employing algorithms and statistical models to evaluate and infer from patterns in data, machines and computer systems can be provided with enough data to learn and adapt without being explicitly instructed. Machine learning (ML) is the term used to describe this method of creating intelligent machines. The use of AI-based tools can be used for a wide range of jobs, from the more straightforward differentiation between cats and birds to more intricate automated production procedures. This article will describe some of the significant applications of AI and ML (Zhao *et al.,* 2021).

Since the creation of CNN, deep neural networks have been effectively used in numerous CV applications, including object categorization, identification, and segmentation. A subset of DNN called CNN is most frequently used for visual analytics. For instance, CNNs have been used to analyse fish habitats with success. CNNs have an important advantage over other image recognition algorithms in that they only need little pre-processing. CNNs aren't manually programmed; instead, they find and pick up hidden elements in the data on their own. Through a variety of levels of abstraction, they learn in steps. For instance, they pick up basic shapes (edges, lines, etc.) in the early stages, more complex patterns in the following levels, and classes of objects in the following layers. (Saleh *et al.,* 2022). The information technology solutions currently used in fisheries and aquaculture are largely based on instrumentation and process control, computerised models, geographic information systems, image processing and pattern recognition, data management, decision support tools, expert systems, artificial intelligence, and information centres / networks (Gladju *et al.,* 2022).

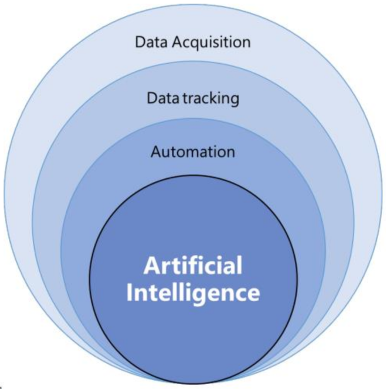


Figure 1. Conceptual diagram showing the role of AI in other digitalisation activities (Fernandes-Salvador *et al.,* 2022)

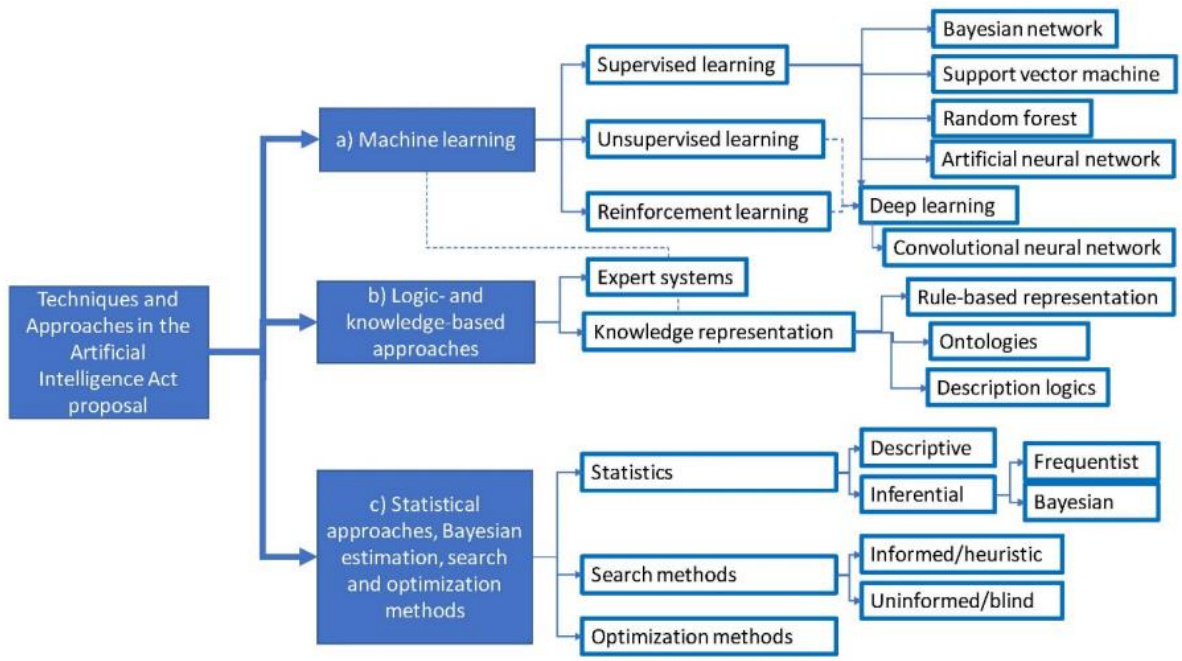
2. The AI revolution

In the 1940s, the first concrete steps towards artificial intelligence were made. Due to six convergent reasons, AI is now a part of our daily lives and has reached a historical moment: 'Big Data' we now have access to enormous volumes of structured (in databases and spreadsheets) and unstructured (such as text, audio, video, and image) data thanks to computers. All of this information records our lives and advances our understanding of the universe. The amount of "big data" will increase as trillions of sensors are installed in furniture, packages, clothing, autonomous vehicles, and other things. By processing this data with AI assistance, we can more effectively predict the future, identify historical trends, generate suggestions, and more. Processing power: Through parallel processing, complex AI-powered systems can now handle massive volumes of data more quickly and affordably thanks to accelerating technologies like cloud computing and graphics is processing units. Future "deep learning" chips, which are now a major area of research, will advance parallel computation. a global network:

3. AI for Biodiversity

Approaches to addressing biodiversity loss include biodiversity research to create an evidence base for action, citizens and local communities managing their ecosystems and resources directly, national and local governments and agencies developing biodiversity protection policy and biodiversity-aligned market frameworks, businesses, and finance institutions acting pro-actively, ahead of policy, to reduce the detrimental biodiversity impact of their products. Biodiversity has severely decreased over the past few decades despite continuous efforts in all of these directions. Natural resource exploitation has a history of outweighing long-term models of sustainable development in favour of immediate financial gain (Li, 2020). When considering how AI might be used to conserve biodiversity, it is important to acknowledge that present methods have not been sufficient and that adding AI to conventional conservation practices is unlikely to yield positive results. Currently, most AI-for-biodiversity applications are concentrated on improving current conservation strategies, albeit on a larger scale than previously done. The most prevalent applications of AI currently in use support biodiversity monitoring by classifying species and landscapes captured by camera traps and satellite images, and to some extent, the monitoring of the drivers of biodiversity, such as by monitoring fishing trawlers or illegal timber logging (Shivaprakash *et al.,* 2022).

4. The classification of AI techniques and approaches in the AIA proposal expanded with further subcategories used in the study: (Kar *et al.,* 2022).



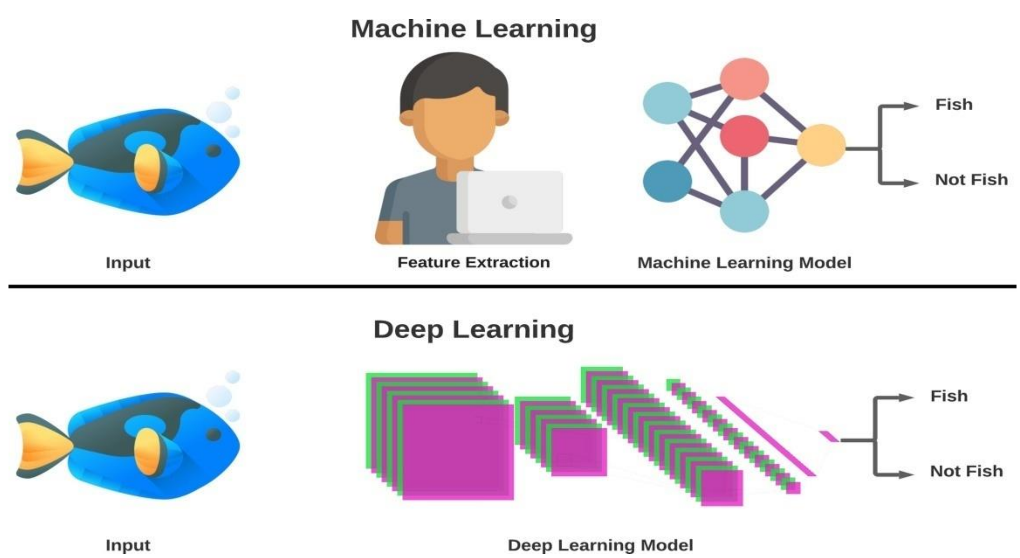


Figure 2. Process of Deep learning in fisheries

5. The Application of Deep- Learning of Marine Fisheries Resource Management

1. Live fish identification

DL is mostly used to determine whether a given object is a fish to identify live fish. DL can be an effective machine vision solution in this day and age where massive volumes of visual data can be quickly gathered. To examine quick and precise techniques, it is worthwhile to investigate the performance levels that can be attained by fusing DL with machine vision (Paraschiv *et al.,* 2022).

Figure 3. Live fish Identification

2. Species classification

Several fundamental morphological characteristics, including the form of the body and the scales, can be used to classify species. The majority of DL models outperform conventional methods, with classification accuracy on the LifeCLEF 14 and LifeCLEF 15 benchmark fish datasets over 90% (Iqbal *et al.,* 2021).

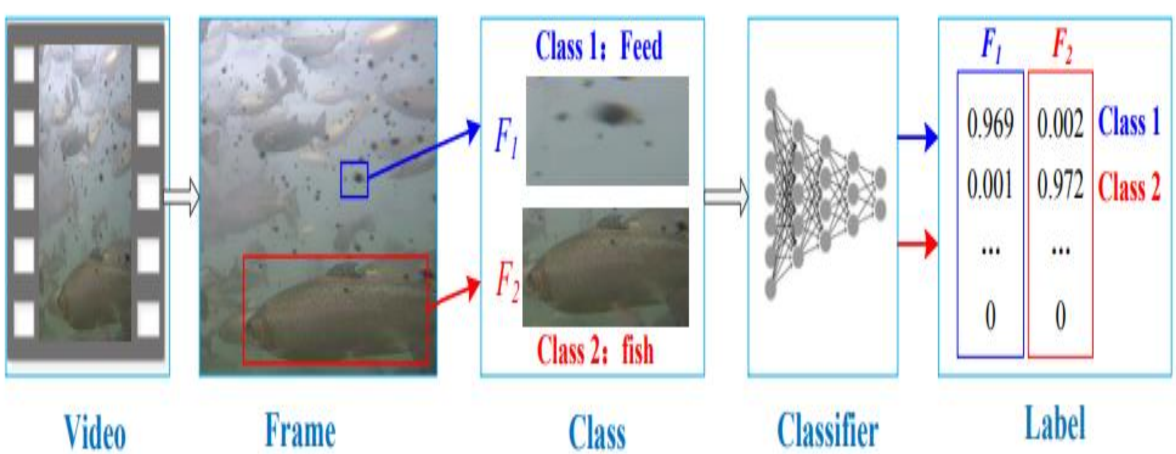


Figure 4. Species classification

3. Behavioral analysis

Additionally, fish welfare and harvesting are effectively referenced using behavior. A nondestructive understanding and an early warning of fish status can be obtained by relevant behavior monitoring, particularly for atypical behaviors. Monitoring fish behavior in real-time is crucial for determining their condition and for making decisions about when to catch and feed them. The ability of DL techniques to recognise visual patterns is considerable. employing DL to analyse behavior. RNNs, in particular, can solve the aforementioned issue successfully because of their strong modeling capabilities for sequential data (Yang *et al.,* 2021).

4. Size or biomass estimation

When maintaining a fish farm, it is crucial to regularly monitor fish factors like abundance, quantity, size, and weight. Scientific fishery management and conservation techniques for sustainable fish production are built on quantitative estimates of fish biomass. When machine vision and DL are used together, fish morphological properties including length, width, weight, and area can be estimated more precisely. Most applications that have been reported have either been monitored or semisupervised. To estimate the size of fish, for instance, the Mask R-CNN architecture was employed (Albuquerque *et al.,* 2019).

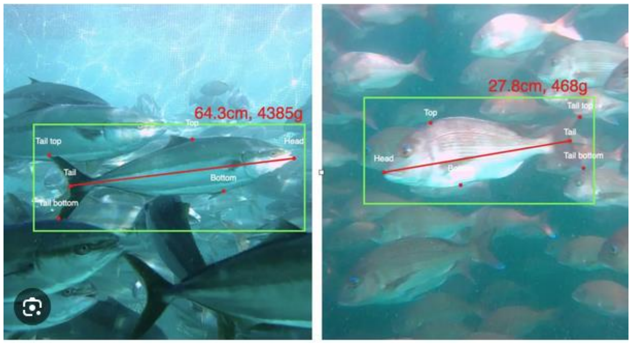


Figure 5. Size measurement

5. Feeding decision-making

The quantity of food fed to fish directly affects both the cost and the productivity of intensive aquaculture. For some fish types, the cost of the feed makes up more than 60% of the whole production cost. The physiological, nutritional, environmental, and husbandry aspects that affect fish feeding, however, make it challenging to identify the true demands of fish. The majority of current research on feeding decision-making using DL has mostly been on image analysis. A better feeding strategy that takes into account fish behavior can be produced using machine vision. A system like this can end the feeding process at more sensible periods, cutting down on wasteful labor and enhancing fish well-being (Zhou *et al.,* 2018).

6. Water quality prediction

To spot anomalous behaviour, stop disease, and lower the dangers to fish, it is critical to be able to predict changes in water quality indices. Time is a key factor in the prediction of dissolved oxygen and other water quality indicators. When given the necessary attention, LSTM, DBN, and other DL models can effectively mine the time sequence information and produce good outcomes. Therefore, a key area for advancement in tasks involving the prediction of water quality will be how to employ DL models to minimise or lessen the adverse effects of uncertainty factors on prediction results (Chen *et al.,* 2020).

7. AI and Fishing

Assessing the economics of commercial fleets, electronic capture, and bycatch monitoring, identifying and forecasting fishing regions, and modelling the behaviour of fishing vessels. They base their definition of what might be referred to as AI technology on "tracing back to the source of catching with the existing data and technology", such as tracing big catch via unlawful catch methods (Khokher *et al.,* 2022).

8. AI prevent the illegal, unreported, and unregulated (IUU)

Promotes transshipments at sea and illicit, unreported, and unregulated (IUU) fishing. Based on the analysis of various data types (signals, pictures, tabular data) obtained from a variety of sources (such as CCTV, AIS, VMS, CSR, UUV, and UAV) (Zuzanna *et al.,* 2022).

9. AI control and monitoring the ghost fishing gear

UAVs, underwater cameras, and UUV sonar or laser scanning technologies can detect ALDFGs. An automated gillnet monitoring system was built in using data from simulations conducted under various climatic circumstances and an ANN-based machine learning system (Thorbjørnsen *et al.,* 2023).

10. AI coral monitoring

Utilising a convolutional neural network, a cutting-edge deep learning tool, to automatically extract the important information from these images. This mathematical model learns to recognise things in images by mimicking neural connections seen in the brain. The software must first be taught to distinguish coral frames, Acropora fragments, and dead fragments (Gonzalez-Rivero *et al.,* 2020).

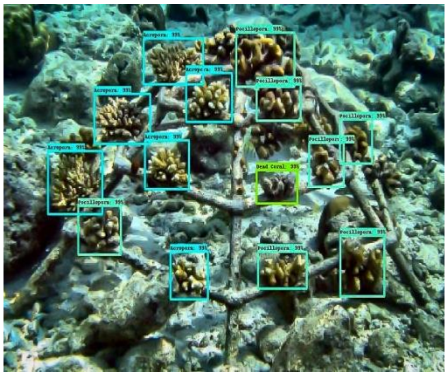


Figure 6. Coral identification

11. AI Pollution control

The most exposed portion of a coral reef in Barbados, discovered by a robotic boat, is vital for determining the effects of climate change. By automating operations that gauge environmental risks and energy efficiency, robots have improved manufacturing. Robots can evaluate the levels of toxicity in factories and the field using IoT-based monitoring (Hoang *et al.,* 2022).

Figure 7. Pollution detection

12. AI and Monitoring Fish Stock

The research that falls under the heading of fisheries resources are those that specifically address the part played by AI in counting fish species. There are various advantages to using AI to count fish species. Researchers can gather information on fish abundance by segmenting, detecting, and classifying fish populations in marine ecosystems. Many publications focus heavily on categorization automation. AI technologies are used to automate the classification of fish. Some academic articles focus on fish detection technology. These systems, which are built on deep network topologies, are capable of detecting and counting fish items under a variety of benthic backdrop and illumination conditions. Although there are certain similarities between the categorization, detection, and identification of fish populations, in practice these automation subjects are the same.

13. AI for improving timely observation and catch-monitoring

In-trawl camera systems are being used by certain fisheries. However, these systems have only been used for research monitoring until operational AI systems have been deployed. The catch monitoring methods that have been developed include extensive human processing and video data preservation. To be effective as decision-support aids, these systems require automated data processing. Fishing is one of many industries that have recently seen an increase in the use of automated processes. Using DL model applications, automatic fish detection and classification are presented in many studies. These studies demonstrate that DL models for item recognition and classification are efficient processing techniques for catching recordings captured underwater and aboard vessels.

14. AI in Conservation of Endangered Fishes

Aquatic animal populations are rapidly falling as a result of human activity. Despite several conservation efforts, it is difficult for people to monitor them due to the open water. Thanks to vision sensors and cameras, AI drones can track endangered fishes and study their habitat far more quickly than humans can. Transmitters can be fastened to the fins of humpback whales and other large species, including sharks, to allow for monitoring. This preserves more of an organism's behavior and makes it much easier to study it (Wahab *et al.,* 2012).

6. Advantages of AI in Fisheries

It encourages more efficient management of aquaculture and sustains high precision in disaster forecasting (disease outbreak or reduction in water quality). AI can be used to improve all areas of fisheries science, from hatcheries to packaging in processing facilities. Productivity increases as a result of less input waste. The AI system can provide a range of solutions as it gains expertise (Kassem *et al.,* 2021).

7. Disadvantages of AI in Fisheries

Despite growing more advantageous, AI has several disadvantages. Many people are unable to make the much larger investments necessary for AI. An AI system has substantial maintenance costs as well. A significant disadvantage of AI is that it eliminates employment opportunities for workers. Farmers may profit from this, but others whose means of subsistence depend on the fishing business would suffer (Li *et al.,* 2022).

8. Conclusion

Automated monitoring, especially in areas where systems are changing as a result of anthropogenic influences, can give managers a thorough, affordable, and continuous supply of accurate information for long-term monitoring and optimal, adaptive management decisions. The unprecedented amount of data that is becoming available, combined with improvements in ML over the last few years, can give managers and researchers the tools to create precise and flexible predictions, despite the current technological and social challenges facing the implementation of AI and automated systems in management. Applying extra analysis and decision assistance to an adaptive management framework will guarantee appropriate and effective management outcomes. However, before these technologies are incorporated into fully end-to-end automated monitoring systems, there are still several study areas that require additional examination of the viability and scalability of these technologies. Despite this, "semi-automated" systems are already feasible and may help with immediate improvements in information because different technologies can be implemented at different phases. The use of technology that is more widely available and accessible can promote adoption, improve management results, and increase a general understanding of marine ecosystems and ecological processes for conservation.

9. References

Albuquerque, P.L.F., Garcia, V., Junior, A.D.S.O., Lewandowski, T., Detweiler, C., Gonçalves, A.B., Costa, C.S., Naka, M.H. and Pistori, H., 2019. Automatic live fingerlings counting using computer vision. *Computers and Electronics in Agriculture*, *167*, p.105015.

Chen, Y., Song, L., Liu, Y., Yang, L. and Li, D., 2020. A review of the artificial neural network models for water quality prediction. *Applied Sciences*, *10*(17), p.5776.

Fernandes-Salvador, J.A., Goienetxea, I., Ibaibarriaga, L., Aranda, M., Cuende, E., Giuseppe, F.O.T.I., Olabarrieta, I., Murua, J., Prellezo, R., Iñarra, B. and Quincoces, I., 2022. Research for PECH Committee: Artificial Intelligence and the fisheries sector.

Gladju, J., Kamalam, B.S. and Kanagaraj, A., 2022. Applications of data mining and machine learning framework in aquaculture and fisheries: A review. *Smart Agricultural Technology*, *2*, p.100061.

Gonzalez-Rivero, M., Beijbom, O., Rodriguez-Ramirez, A., Bryant, D.E., Ganase, A., Gonzalez-Marrero, Y., Herrera-Reveles, A., Kennedy, E.V., Kim, C.J., Lopez-Marcano, S. and Markey, K., 2020. Monitoring of coral reefs using artificial intelligence: A feasible and cost-effective approach. *Remote Sensing*, *12*(3), p.489.

Hoang, T.D., Ky, N.M., Thuong, N.T.N., Nhan, H.Q. and Ngan, N.V.C., 2022. Artificial intelligence in pollution control and management: status and prospects. *Artificial Intelligence and Environmental Sustainability: Challenges and Solutions in the Era of Industry 4.0*, pp.23-43.

Iqbal, M.A., Wang, Z., Ali, Z.A. and Riaz, S., 2021. Automatic fish species classification using deep convolutional neural networks. *Wireless Personal Communications*, *116*, pp.1043-1053.

Jothiswaran, V., Velumani, T. and Jayaraman, R., 2020. Application of artificial intelligence in fisheries and aquaculture. *Biotica Research Today*, *2*(6), pp.499-502.

Kar, A.K., Choudhary, S.K. and Singh, V.K., 2022. How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, p.134120.

Kassem, T., Shahrour, I., El Khattabi, J. and Raslan, A., 2021. Smart and sustainable aquaculture farms. *Sustainability*, *13*(19), p.10685.

Khokher, M.R., Little, L.R., Tuck, G.N., Smith, D.V., Qiao, M., Devine, C., O'Neill, H., Pogonoski, J.J., Arangio, R. and Wang, D., 2022. Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: where machine learning meets commercial fishing. *Canadian Journal of Fisheries and Aquatic Sciences*, *79*(2), pp.257-266.

Li, C., 2020. Biodiversity assessment based on artificial intelligence and neural network algorithms. *Microprocessors and Microsystems*, *79*, p.103321.

Li, D., Wang, G., Du, L., Zheng, Y. and Wang, Z., 2022. Recent advances in intelligent recognition methods for fish stress behavior. *Aquacultural Engineering*, *96*, p.102222.

Lim, L.W.K., 2022. Implementation of Artificial Intelligence in Aquaculture and Fisheries: Deep Learning, Machine Vision, Big Data, Internet of Things, Robots and Beyond. *Journal of Computational and Cognitive Engineering*.

Paraschiv, M., Padrino, R., Casari, P., Bigal, E., Scheinin, A., Tchernov, D. and Fernández Anta, A., 2022. Classification of underwater fish images and videos via very small convolutional neural networks. *Journal of Marine Science and Engineering*, *10*(6), p.736.

Saleh, A., Sheaves, M. and Rahimi Azghadi, M., 2022. Computer vision and deep learning for fish classification in underwater habitats: A survey. *Fish and Fisheries*, *23*(4), pp.977-999.

Shivaprakash, K.N., Swami, N., Mysorekar, S., Arora, R., Gangadharan, A., Vohra, K., Jadeyegowda, M. and Kiesecker, J.M., 2022. Potential for artificial intelligence (AI) and machine learning (ML) applications in biodiversity conservation, managing forests, and related services in India. *Sustainability*, *14*(12), p.7154.

Thorbjørnsen, S.H., Synnes, A.E.W., Løset, I.D. and Kleiven, A.R., 2023. Hazard and catch composition of ghost fishing gear revealed by a citizen science clean-up initiative. *Marine Policy*, *148*, p.105431.

Wahab, A., Saeed, K., Azam, M. M. and Nasir, S. M. 2012. "Distribution and Status of Threatened Species of Freshwater Turtles in Selected Areas of Indus River System." Zool. Surv. Pakistan. 1-53.

Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D. and Chen, Y., 2021. Computer vision models in intelligent aquaculture with emphasis on fish detection and behavior analysis: A review. *Archives of Computational Methods in Engineering*, *28*, pp.2785-2816.

Zhao, S., Zhang, S., Liu, J., Wang, H., Zhu, J., Li, D. and Zhao, R., 2021. Application of machine learning in intelligent fish aquaculture: A review. *Aquaculture*, *540*, p.736724.

Zhou, C., Xu, D., Lin, K., Sun, C. and Yang, X., 2018. Intelligent feeding control methods in aquaculture with an emphasis on fish: a review. *Reviews in Aquaculture*, *10*(4), pp.975-993.

Zuzanna, K., Tomasz, U., Michał, G. and Robert, P., 2022. How high-tech solutions support the fight against IUU and ghost fishing: a review of innovative approaches, methods, and trends. *IEEE Access*.