Artificial Intelligence that Learns Fish Behavior Might Improve Fishing Gear

[1]Shweta Saraswat, [2]Shefali Sharma, [3]Nootan Verma , [4] Shashi Sharma , [5] Monica Lamba

[1]Asst. Prof. Department of Artificial Intelligence and Data Science, Arya Institute of Engineering and Technology, Jaipur, Rajasthan.

[2]Asst. Prof. Computer Application , JECRC university, Jaipur, Rajasthan

[3]Asst. Professor Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan

[4]Asst. Professor Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan

[5] Asso. Professor Department of Computer Science and Engineering, Arya Institute of Engineering and Technology, Jaipur, Rajasthan.

Abstract: Researchers have used monitoring devices to examine fish behavior in the vicinity of fishing gear. Deep learning algorithms allow marine scientists to quickly analyze massive amounts of image data (AI) documenting fish behavior. New artificial intelligence (AI) algorithms can identify and classify fish species with near-human precision, but reliable techniques for observing fish in their natural habitats, particularly tropical species, are still lacking. Interactions between fish and fishing gear are extremely uncommon, especially for temperate species. As part of this study, we looked at how advanced fish monitoring, categorization, and behavior recognition systems powered by AI may improve the selection of fishing equipment. It analyzes the progress of AI as well as the opportunities and constraints it faces in order to comply with fishing regulations and sustainable goals. This discovery has the potential to transform the fishing industry for the benefit of fishers, the environment, and the economy.

K**eywords**: Fisheries, Gear Technology, Artificial Intelligence, Deep Learning

1. Introduction:

The ability to see fish well with the naked eye Thanks to the advancement of non-intrusive and autonomous underwater video camera technology, a wealth of high-resolution marine images and movies may now provide insights into marine animal behavior. Fish interactions with fishing equipment, including pots, lines, trawls, and nets, may now be captured on camera in 2D or 3D. This has made it possible for scientists to examine fish behavior in novel settings. New selection and bycatch reduction methods are constantly being included in gear designs as gear selectivity increases. The analysis of the effects of these alterations has shown tighter patterns of selectivity, highlighting the importance of tactile, aural, and visual information in fish capture.

Studies on fish vision have shown that each species' sensitivity to various hues varies. Lights and colors are being added to gears to make them more visible. Despite the fact that the mesh and panel patterns have an impact on both tactile cues and herding behavior, different animals may respond to them differently. [1] The impacts of sight, hearing, and handling on fish behavior have been extensively studied. In order to guide migratory pathways via river crossings, perform stock evaluations, and monitor fish health in fish farms, automatic fish identification techniques have mostly been created for commercial benefits. Although artificial intelligence (AI) has evolved into a potent data processing tool in marine studies, the majority of studies continue to concentrate on the two-dimensional temporal features of swimming behavior. but without accounting for the depth and 3D characteristics of the actual environment.

Studies on fish eyesight have revealed that each species has a unique sensitivity to different colors. Gears are being painted and given lights to increase their visibility. The construction of the mesh and panel pattern affects tactile signals and herding behavior; however, different animals may respond to them differently.[2] Numerous studies have been done on how hearing, sight, and handling affect fish behavior. Automatic fish identification systems have mostly been developed for commercial purposes in order to undertake stock assessments, direct migratory paths across river crossings, and track fish health in fish farms. The bulk of research continues to focus on the two-dimensional temporal aspects of swimming behavior, despite the fact that artificial intelligence (AI) has developed into a powerful analysis tool in marine studies. Nevertheless, without taking into consideration the vastness and 3D aspects of the real world.

Most digital fish ID systems were developed with commercial use in mind. They assist in directing migratory routes across narrow river passages, conducting stock assessments, and monitoring aquaculture facilities for fish health. Most marine research studies currently only consider the temporal features of movement behavior on a 2D scale, despite the fact that AI has become a powerful tool for managing data in this field. They don't give the world's spatial depth and three-dimensional features any consideration. It is possible to translate what the human eye perceives and comprehends using computer vision and artificial neural networks. In order for the system to make sense of the information, the fish photos must be transformed into statistical models that account for both time and location.

The science of fish observation has advanced significantly over the last ten years, resulting in the creation of algorithms that can precisely and automatically recognize fish in films, identify species, and track their swimming orientation. [3]These developments have improved the effectiveness of fish observation while also enabling better knowledge of the behavior of fish and migratory patterns, which may guide the administration of fisheries and conservation initiatives. But there is still a lot to be discovered and developed in this area.

II. Stimulus-response studies with fishing gear to train AI behavior recognition models

Recent research has shown that fish display a wide range of sophisticated behaviors, similar to other vertebrates, and that learning is essential to fish's maturation into adults. Fish are no longer thought of as simpleton creatures with little intelligence and unpredictable behavior.

a) Impact of fishing gear on fish behavior as observed

Selective devices and modifications to commercial fishing gear were implemented after preliminary testing, which included methods like as hand counting, size measurements, and quantifying catches and retention. Changes to the mesh have been proposed using a variety of techniques, including tank experiments and computer modeling. Catch estimates and species activity in gear have been tracked using optical and sonar surveillance. To increase size and breed selectivity, researchers have developed unique gears with larger meshes and strategically placed sorting grids as a result of a better understanding of fish reaction and escape behavior.[4] Integration of tactile, auditory, and visual inputs to elicit active species responses may also increase gear selection.

b) Current observations of fish stimuli and responses

Fish respond well to visual, aural, and olfactory inputs. Fish are intriguing organisms that respond to their surroundings in many ways. Research on fish-environment interactions may impact conservation and management efforts.

i) Reactions to various light and color stimuli

Fish light sensitivity has been studied in aquariums and aquaculture, but due to light attenuation, it is difficult to study in the wild. Using artificial lights, fish are guided to safety, dissuaded from entering gears, and helped to flee. Fish have more accurate color vision than humans because of their tetrachromatic vision. Researchers use species-selective traits to accomplish tasks like adding lights to equipment or painting fishing nets a different color.

ii) Reactions to acoustic stimuli

Some fish are more attuned to various frequencies and may be selected using sound. Passive acoustic approaches may have gears added to them to make them more noticeable to animals that utilize echolocation with the use of sound reflectors. The hunt for reliable, species-specific tools is still in its infancy.

iii) Reactions to physical stimuli

Changes can be made to the mechanical structures and gear panels by copying a fish's natural tendency to move close to the bottom. This is called thigmotaxis. The way water moves in a certain way, which is called rheotaxis, can be used to make trawls more selective. Veil nets used in shrimp fishing can change the way water flows through gears and direct fish to certain grids and net structures. However, water jets those shoot out from below or in front of the gear can help fish escape before it's too late.

iv) In addition to or in tandem with other stimuli

Fish use chemotaxis and electrotaxis to detect objects at longer distances. Longline fishing uses chemotaxis and electrotaxis to reduce bycatch. When fish are exposed to several sensory inputs at once, including sounds and images, they display a wide range of behaviors. Insight into the sensory systems of marine animals might lead to improvements in catch-selective gear, reductions in bycatch, and targeted catches.

III. Artificial intelligence applied to fish stimuli

Experiments are the best way to learn about the reactions of fish to different stimuli. Unfortunately, repeating an experiment is not always possible due to time and resource restrictions. Now, we can tell what kind of behavior someone is exhibiting by watching how they react to a certain stimulus. AI models might simplify data management and open the door to using more information. Since deep learning methods are more robust, they can function in more demanding environments. Improving computer vision also involves selecting the viewing mode that provides the most relevant image data for the equipment being utilized.

a) Artificial Intelligence: An Introduction

Artificial intelligence (AI) and deep learning are influencing the future of fisheries research. Influence is also being exerted by the Internet of Underwater Things (IoUT) and big data. In marine science, many of the neural networks used for item identification are "supervised," meaning they learn to recognize certain types of things by being exposed to examples of those types of objects in real-world contexts and being given labels by humans. Sorting an item into one or more categories is possible if the model's predictions regarding the object's categorization are accurate.[5] Once their locations have been established over several frames, the tracking model will use the links between the bounding boxes in each frame to calculate the path taken by each item over time. Predictions of classes and bounding boxes from a trained model are judged accurate if they deviate from the ground-truth validation data by no more than a predetermined threshold. Artificial neural networks use a number of mathematical operations (convolution, pooling, etc.) to recognize objects and are used in simplified versions of computer systems that extract information from pictures. The techniques may be able to recognize an item by inspecting its picture data for unique patterns that reveal its properties. Automatic pattern recognition based on their properties is possible with the help of [6] detection algorithms. Before being used to train a model, the images are preprocessed to enhance their quality. More and more modern artificial neural networks have attention units, enabling them to recognize global relationships and far-flung connections inside pictures. In their current form, most deep learning algorithms are "black boxes," hiding the underlying neural network that generates the output from the user. That's why it's crucial to evaluate different sets of training data and prioritize high-quality inputs when building a model. Curiosity in autonomous learning is on the rise as people want to go beyond simple recognition into deeper levels of understanding.

In light of recent advances in AI, models that can provide explanations for their conclusions about object localization and categorization have become available. The two main components of a GAN are the generator, which creates fake data, and the discriminator, which determines whether or not the input is genuine.[7] Semi-supervised learning is possible when an object detector is connected with a GAN, which generates fresh data sets of pictures to be processed by the object detector. Applying the same artificial intelligence techniques to the interactions between fish and fishing gear might lead to a far more in-depth understanding of the causes of catch-and-release rates.

b) Artificial intelligence for fish behavior

Automatic behavior recognition technologies are primarily being developed for use with aquaculture and coastal fish populations. Advances in automatic fish identification, species categorization, and tracking over the last decade have provided a solid foundation for behavioral identification. Mechanical sensing was used to learn a variety of things about their habits, such as how much and what they ate, whether or not they were behaving abnormally due to lack of oxygen or stress, and whether or not they were investigating objects or food out of pure curiosity.[8] Computer vision has also been used in lab experiments to automatically detect and label goal-directed activities in fish. Artificial intelligence approaches have been trained to comprehend fish behavior, and to do so need a complex web of interconnected mathematical and statistical procedures. Numbers may be obtained from a film of swimming fish by analyzing the fish's form, texture, and color, as well as their reactions to various stimuli.

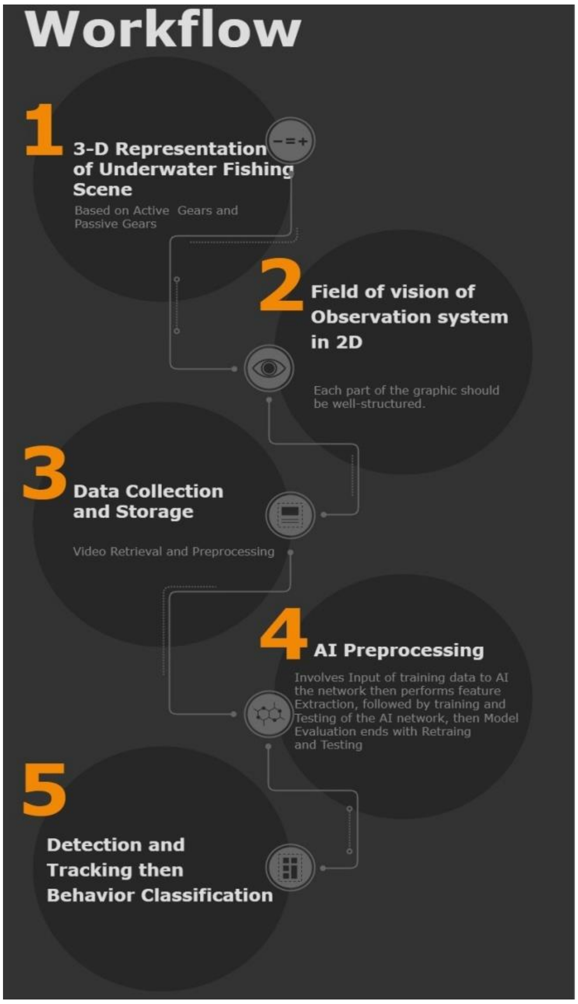

Fig. 1: Diagram of Workflow

c) Artificial intelligence-based fish behavior recognition

Artificial intelligence systems can identify many fish species from a single photograph. Fish species in 2D photos have been identified and categorized using the YOLO (You Only Look Once) object identification framework. [9]Targeted and untargeted species may be distinguished using a detection algorithm that has been taught to recognize morphological differences between the two groups and show how crowd dynamics are indicative of flocking behavior. Until they disappear from view, fish are followed using motion algorithms trained on picture sequences of many or single fish. Depending on the monitoring goals of the study or the available resources, researchers have useda variety of deep learning-based tracking systems.

To keep track of and make sense of more granular behavioral data, AI pipelines make use of coupled networks. In order to examine the underlying behavioral patterns of fish, fish tracks may be made either manually or mechanically, and the repetitive patterns within them can be translated into sets of labeled classes. Artificial intelligence (AI) has been used to automate the categorization of manual behavior in aquaculture and industrial fishing. A systematic strategy in controlled settings, such as fish tanks or behavioral chambers, may be necessary for AI algorithms to categorize these interactions. Since these recurrent AI models built on LSTM architecture are intended to favour meaningful movement patterns over erratic ones as they are taught, they are receiving a lot of attention.

The development of AI attention and memory is critical in fishing operations because it facilitates the management of chaotic patterns between species throughout the capturing process. The distance between gear structures, the average trajectory in respect to the stimulus source, and differences in the group or individual trajectories inside gears may all be revealed by analyzing the tracks left behind. By fusing the tracking data's spatiotemporal characteristics with the automated detection data's visual features, behavior may be classified.

IV. AI-adapted behavioral classes

The ability of a model to recognize fish behaviors is defined as the ability to do so via the observation of attributes that may be clustered into occurrences. It's possible to capture and observe firsthand events like a school of fish breaking loose of fishing gear. The last stage in translating random fish movement into defined behaviors is automatic behavior recognition, which is taught using categorized sets of tracking data. In order to identify an activity in a moving image or video sequence, researchers categorize actions into categories. Video of a fish swimming through a net, for instance, may be annotated to show that it engaged in escapement activity. [10]

If the tracked fish's trajectory continues within the mesh barrier after it has been discovered outside the gear, it has either fled or is still trapped inside. Whether or not a fish is judged to have fled depends on the researchers' categorization decisions. In order to quantify the peculiar behaviors seen in sablefish trajectories, [11] proposed four criteria. They combined the four features into one coherent whole that could be utilized to teach an LSTM classifier by means of AI. In studies of selectivity, researchers have employed empirical models or video-tracking detection methods to characterize different kinds of behavior. The use of a three-step process to identify fish exhibiting anomalous behavior in the wild [12].

a) The issue of occlusion is highlighted in the crowded fishing scenes.

Fish swimming next to or behind one another cause occlusion, which lowers the number of fish detected and shatters the tracks. It may be possible to eliminate fish occlusion in 2D images and films by teaching computers to recognize certain fish sections. Fish heads are often hidden, but their forms and colors are generally consistent, making it simple to identify them from frame to frame. Occlusion issues could be alleviated by three-dimensional tracking from stereo cameras or many camera systems with triangulable 3D components. Reidentification after a blockage is made easier with the use of three-dimensional reconstruction of fish trajectories. However, for AI models trained to recognize 3D motions, joining the deconstructed pieces together requires computationally expensive procedures. [13]

b) Adaptive learning in the face of limited data

We demonstrated the importance of analyzing fish activity trajectories and how they may be used to train computers to detect fish in murky water. We used the public Fish4Knowledge (F4K) dataset for model training. Since the program's launch in 2010, millions of GoPro photographs and more than 145,000 distinct fish have been recognized. [14] The current models can only accurately identify a portion of the temperate fish species that are the focus of commercial fishing, despite their rising popularity. In [15], writers trained an artificial intelligence pipeline to find and monitor sablefish, Anoplopoma fimbria, in a North American underwater canyon using 650 hours of video and 9000 human comments. Certain fish species may be recognized by current AI models with accuracy comparable to humans. These include species from the mesopelagic region as well as the Scythe butterfly fish and several tropical species. Automated detection pipelines have used transfer learning and data augmentation techniques to address the data shortage.[16] Employed transfer learning to train AI to recognize two economically significant species of temperate fish, wrasses and gadoids.[17] By using transfer learning from existing item identification algorithms strengthened with data from other contexts, autonomous fish species analysis may be feasible even in locations with little data at the moment. In the lack of small datasets, additional augmentation techniques, such as the production of synthetic datasets, may be used to train models.

V. Conclusion:

Fish behavior in the wild and on farms may be better understood by ecologists and computer scientists. While marine scientists give the data and expertise to guide the study, AI specialists provide the fundamental biological challenge and components required to fine-tune the algorithms. Using AI to track the environment could hasten data collection for citizen science. Scientists are using FAIR data to build a single database and better interpret fish behavior data. Building secure automated fish monitoring systems more quickly may be made possible by sharing data, accessing databases, and developing collaborative websites. Electronic fishing using AI is still in its infancy, but it has the potential to improve gear. The quality of artificial intelligence models depends on the training set that was used. Both ground-based and airborne behavioral studies have a great deal of promise for using AI to automatically identify behavior. However, such systems' environmental implications must be considered. Before using AI in fishing, it is necessary to do study on the potential effects. It might be seen as having two sides since it could help the fishing industry and academics learn more about fish behavior and find ways to reduce bycatch. To prevent misuse, stakeholders must weigh the benefits and drawbacks of AI and agree on an ethical standard.

VI. Recommendation

The analysis of fish-gear interactions is hampered more by an excess of data than a lack of it. Scientists may be able to devote their time and energy to more in-depth research and innovative initiatives if data collection and processing methods could be automated. The rapid progress of AI models will surely have an impact on the development of fishing models. Several factors, such as researchers' willingness to provide information on fish behavior and the precision with which trajectory data is classified, will determine the success of future artificial intelligence models for automatically recognizing fish-gear interactions.[18] It will also be necessary to modify and retrain pre-existing models gleaned from many studies of human and animal behavior. No miraculous tool exists that simultaneously selects just the desired species, prevents the escape of all unwanted species, and incurs no costs or biological losses. However, as we enter the modern era, installing fishing gear with cutting-edge technology may help resolve ecological difficulties, understand the behavior of unrecognized species, and increase the long-term viability of our fishing practices.

References:

[1] P. Zhuang, Y. Wang and Y. Qiao, "Wildfish++: A Comprehensive Fish Benchmark for Multimedia Research," in *IEEE Transactions on Multimedia*, vol. 23, pp. 3603-3617, 2021, doi: 10.1109/TMM.2020.3028482.

[2] Mandralis, I., Weber, P., Novati, G., & Koumoutsakos, P. (2021, September 20). Learning swimming escape patterns for larval fish under energy constraints. *Physical Review Fluids*, *6*(9). https://doi.org/10.1103/physrevfluids.6.093101

[3] Fisher, R., Chen-Burger, Y.-H., Giordano, D., Hardman, L., and Lin, F.-P. (Eds.). (2016). Fish4Knowledge: Collecting and analyzing massive coral reef fish video data 104, 319. Berlin Heidelberg, Germany: Springer. doi: 10.1007/978-3-319-30208-9

[4] Alshdaifat, N. F. F., Talib, A. Z., & Osman, M. A. (2020, September). Improved deep learning framework for fish segmentation in underwater videos. *Ecological Informatics*, *59*, 101121. https://doi.org/10.1016/j.ecoinf.2020.101121

[5] Banerjee, S., Alvey, L., Brown, P., Yue, S., Li, L., & Scheirer, W. J. (2021, January 13). An assistive computer vision tool to automatically detect changes in fish behavior in response to ambient odor. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-020-79772-3

[6] Aziz, L., Haji Salam, M. S. B., Sheikh, U. U., & Ayub, S. (2020). Exploring Deep Learning-Based Architecture, Strategies, Applications and Current Trends in Generic Object Detection: A Comprehensive Review. *IEEE Access*, *8*, 170461–170495. https://doi.org/10.1109/access.2020.3021508

[7] Yuan, H., Zhang, S., Chen, G., and Yang, Y. (2020). Underwater image fish recognition technology based on transfer learning and image enhancement. J. Coast. Res. 105, 124–128. doi: 10.2112/JCR-SI105-026.1

[8] Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X., et al. (2019). Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision. Aquaculture 507, 457–465. doi: 10.1016/J.AQUACULTURE.2019.04.056

[9] Barreiros, M. D. O., Dantas, D. D. O., Silva, L. C. D. O., Ribeiro, S., & Barros, A. K. (2021, February 5). Zebrafish tracking using YOLOv2 and Kalman filter. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-81997-9

[10] Huang, K., Han, Y., Chen, K. *et al.* A hierarchical 3D-motion learning framework for animal spontaneous behavior mapping. *Nat Commun* 12, 2784 (2021). https://doi.org/10.1038/s41467-021-22970-y

[11] Saleh, A., Laradji, I.H., Konovalov, D.A. *et al.* A realistic fish-habitat dataset to evaluate algorithms for underwater visual analysis. *Sci Rep* 10, 14671 (2020). https://doi.org/10.1038/s41598-020-71639-x

[12] Wang, J. H., Lee, S. K., Lai, Y. C., Lin, C. C., Wang, T. Y., Lin, Y. R., et al. (2020). Anomalous behaviors detection for underwater fish using AI techniques. IEEE Access 8, 224372–224382. doi: 10.1109/ACCESS.2020.3043712

[13] Bonofiglio, F., de Leo, F. C., Yee, C., Chatzievangelou, D., Aguzzi, J., and Marini, S. (2022). Machine learning applied to big data from marine cabled observatories: A case study of sablefish monitoring in the NE pacific. Front. Mar. Sci. 9. doi: 10.3389/ fmars.2022.842946

[14] Knausgård, K. M., Wiklund, A., Sørdalen, T. K., Halvorsen, K. T., Kleiven, A. R., Jiao, L., et al. (2021). Temperate fish detection and classification: a deep learning based approach. Appl. Intell. 52(6), 6988–7001. doi: 10.1007/s10489-020-02154-9

[15] McIntosh, D., Marques, T. P., Albu, A. B., Rountree, R., and de Leo, F. (2020). Movement tracks for the automatic detection of fish behavior in videos. arXiv preprint arXiv:2011.14070. doi: 10.48550/arXiv.2011.14070

[16] Yu, X., Wang, Y., An, D., and Wei, Y. (2021). Identification methodology of special

behaviors for fish school based on spatial behavior characteristics. Comput. Electron Agric. 185, 106169. doi: 10.1016/j.compag.2021.106169

[17] Abangan, A. S., Kopp, D., & Faillettaz, R. (2023, January 31). Artificial intelligence for fish behavior recognition may unlock fishing gear selectivity. Frontiers. https://doi.org/10.3389/fmars.2023.1010761

[18] Zhang, L., Li, W., Liu, C., Zhou, X., and Duan, Q. (2020). Automatic fish counting method using image density grading and local regression. Comput. Electron Agric. 179, 105844. doi: 10.1016/J.COMPAG.2020.105844