Tracking of Fish Behaviour Using Computer Vision and Deep Learning

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Abstract

Deep Learning is expanding its application area and developing interest in processing techniques, visualization and feature extraction when compared to Machine Learning Algorithms. Deep learning methods have made it possible to create more efficient and sophisticated models of computer vision. The usage of computer vision applications is now becoming immensely important since these technologies advance. While using CV models to process the visual data sometimes it adds many layersto give expected output. To diminish this problem Neural Networks are used to progressively reduce the input data and calculate the most relevant data. With such rapid development of visual data processing techniques using Deep Learning it has become popular in many fields along with Aquaculture. This emerging techniques were applied on aquaculture and helped in developing the methods on fish farming, fish analysis, and detecting species of fish, or any aquatic animals and also used in fish behavior, water toxic analysis, etc. in this proposed system we use Deep Learning and Computer Vision techniques to predict fish behavior in different conditions like feeding, hypoxia, hypothermia, frightening, and normal. To obtain a data set of accurate precision we have a small setup a RGB camera to record the behaviors. All these data is processed with neural networks and computervision techniques and compares the accuracy rate of each technique and noted as a part of experimentalong with fish behavioral statistics under different conditions. To detect the fishes easily and concentrate on them we also used YOLO object detection algorithm. The results of precision, recall, specificity, and accuracy of the model on five different behaviours of fish are shown.

Key words: Neural Networks, Deep Learning, Computer Vision, Fish Behavior, YOLO, RGB.Introduction

Living organisms constantly sense and analyze the surroundings they live in. This involves both inorganic and organic creatures. Everything is done with the goal of making conclusions and reacting, whether consciously or subconsciously. Fish behavior is an important and complex subject. The nature of an individual fish's response to specific stimuli out of its environment, like in nearly all creatures with a central nervous system, is determined by the hereditary qualities of its central nervous, what has been learnt from prior experience, as well as the nature of stimuli. In comparison to the diversity of human reactions, a fish's reaction is conventional, not susceptible to much alteration by "thinking" or learning, and researchers must avoid humanistic explanations about fish behavior.

Fishes observe their surroundings through their normal senses of hearing, smell, sight, taste, and touch, as well as specific dorsal side water-current sensors. A technique known as electro location enhances perception in the few fishes that produce electric fields. Based on the fish's other characteristics, one or more of these senses is frequently accentuated at the expense of others.

Over the last 2 decades, need for aquatic products has expanded fast due to rapid expansion in the world population. This fast expansion has had an indirect impact on fish habitat. With the advance of technology and science, more and more pesticides are being utilized across the world, raising concerns about their potential harm to aquatic creatures. Before releasing chemicals onto the market, all chemical businesses must examine their toxicity. Animal testing have typically been used to determine the toxicity of substances. These toxicological tests, however, are mostly not unethical, but also costly, time consuming and labor intensive. Fathead fishes are among the most commonly employed in aquatic toxicology studies, and the 96hLC50, which denotes the 96 hours 50% fatal dose, is utilized as a statistical toxicity endpoints. Water toxic surveillance is a vital and necessary job for risk analysis in marine ecosystems and management of water resources. Sensing disruption (e.g., pollutants or toxicants) in aquatic system is essential for early groundwater resources warning. To trace such brutalities, we employ a variety of methods and modeling techniques for monitoring the fish through video and detecting toxic levels. However, such models must compute and evaluate many elements that influence fish behavior in different circumstances, as well as forecast the hazardous level of both fish and water.

Numerous user defined data sets are necessary for analyzing these models to be efficient, which might restrict the model's use, but current research has focused on the use of machine learning approaches that can solve these limits. Machine learning (deep learning) can analyze and learn from massive amounts of unstructured raw data, extracting essential patterns and delivering insights into many research issues. Furthermore, deep learning's ability to pick the most important characteristics may give data scientists with clear and accurate results. Deep learning techniques have transformed our ability in analyzing videos automatically, which has been applied for fish detection, species identification, weight estimate, water quality and behavior analysis. Deep learning has the benefit of automatically identifying and extract visual features and performing exceptionally well in detecting sequential actions.

In this proposed system we will use several Deep Learning techniques such as Neural Networks, Multi Linear Perceptron (MLP), and Support Vector Machine (SVM) to provide a suitable approach for automatically detecting fish behavior from surveillance videos in real time, laying the groundwork for intelligent view in fish farming. YOLO is used to detect fish in the tank, and the optical flow algorithm is used to detect fish movements. The following are the primary contributions of our work: (1) A novel deep learning-based method is used to recognize fish activities; (2) the proposed model recognizes the five fish behaviors via the feature. The proposed framework performs well and produces satisfying outcomes.

We took some fish and placed them inside a tank designed specifically for experiment, and we continuously monitored them for the anticipated results. We will primarily demonstrate five fish behaviors: normal, such as behaving or swimming in groups appropriately in the entire tank, feeding for consuming bait in clusters, hypoxia for gathering and floating heads in inside of the tank, hypothermia for being inactive by sinking to the bottom of tank, and fearful after experiencing sudden external stimuli such as light or sound and swimming quickly. Despite the fact that there are more behaviors, we only evaluated five with the support of specialists' expertise and experiences.

Literature Survey

Live animal toxicity tests are becoming the standard, with thousands of fish used in each evaluation (Hartung and Rovida, 2009). Various rules have been set within the EU (European Union) for industries to reduce the danger caused by their hazardous goods. The European Medical Agency (EMA) regulates medicines in the EU, and the REACH regulation governs other chemical compounds (EuropeanCommission, 2005; European Medical Agency, 2006).

Since powerful computer vision methods were created and incorporated into behavioral monitoring systems over the last few years, video tracking-based early biological warning systems have made significant development (Bae; Park 2014; Dell, Bender; Bronson et.al 2015). Biological monitoring based on video monitoring is becoming a widespread approach for gathering behavioral datasets. The fundamentals for video tracking exhibit pioneer studies in the exact monitoring of group of people in 2D and 3D space Behavioral detection is critical in risk analysis in aquatic environments. Computer vision models can measure accurate individual behaviors' and bodily states. Occlusion, which occurs frequently, remains the major barrier in many people. Advanced algorithms are being designed to extract specific body features in order to increase the precision of a huge number of people (Xia, Chunlei; Fu, Longwen; Liu, Zuoyi; Chen, Lingxin; Liu, Yuedan; Liu, Hui 2018).

Consider a real-life aquatic environment typically comprises numerous fishes in a same picture, which prevents use of normal classification algorithms when choosing AI methods for monitoring. Object detection prior categorization is one answer to this situation. The object detection phase distinguishes and segregates between objects inside a picture, preparing the image files for classification. Object detection and identification could be two distinct phases in a workflow, or they can be combined as one technique of an object detector, like YOLOv4-YOLOv1. (Connolly et al., 2021, Knausgard et al., 2021, Yang et al., 2021, Jalal et al., 2021, Shin et al., 2021, Bochkovskiy et al., 2020, Redmon et al., 2016).

The CNN is the highest developing network for providing a description to a picture when it comes to vital data processing. A set of pooling and convolution layers operate as automated feature extraction in the group of networks, representing the information stored in original data in a 4 highly significant way. Complicated computer vision applications (object detection, classification, and so on) are simplified as a result of these features. Several models have been recently developed, either modified to provide a description to every pixel or to data series, for instance. (Long et al., 2015, Qi et al., 2017, Karim et al., 2018). In recent times, the institutions have begun to concentrate on the integration of complicated data, such as satellite pictures. Object detection and tracking together can give numerous sources of datasets that can be used to support data-driven decisions that significantly impact the wellbeing and efficiency of marine ecosystems. (Audebert et al., 2019, Marcano-Lopez et al., 2021).

Researchers created computer vision techniques to characterize goldfish activity, paving the path for fish behavior detection Using marine fish populations as the study object, the researchers developed a k-layer feature extraction framework that combined picture recognition and evaluation metrics to achieve two-classification, and then utilized the obtained data to assess fish diversity. For video and image processing, the scenes found in aquaculture provide several obstacles. First, noise, light, and water turbulence all have an impact on image quality, resulting in low resolution and clarity. Second, because fish move freely and are uncontrollable targets, their actions might result in deformations, distortions, overlapping, occlusion and other undesirable effects. (Marini 2018, Zhou et al., 2017a, 2017b, Kato 1999). These issues have a negative impact on most existing image processing algorithms. To improve accuracy of detection for the given application, train the DNN with photos of fish in its natural habitat. Developing a high-performance and reliable fish detection requires collecting and categorizing relevant video and image data. Current, public databases are an important aspect of this study, especially for fish detection and classification (e.g., The datasets of Fish4Knowlege classify fish species and location as in NOAA fishery and OzFish datasets). (Sun et al., 2018; Qin et al., 2016, Fisher et al., 2016, Knausgard et al., 2021, Link et al., 2015, Ditria et al., 2021).

Methodology

Since fishing industry has been around for a long time, experts have conducted numerous studies and experiments on the subject. Fish farms have grown more essential in modern life since they contribute significantly to the economy and maintain a consistent distribution and supply of fish across the world.

Fish farming is a time-consuming operation that necessitates a lot of manual labor. Fish loss is caused by the lack of monitoring, hence automatically monitoring fish farms would reduce the danger of fish loss. Fish Farm attempts to identify any abnormalities in fish ponds, such as fish aberrant behavior, automatically, reducing the danger of fish mortality and increasing fish productivity. If fish are maintained in the waters for ecological reasons, the marine life benefits as well. Every one of the experiments involve studying fish behavior over a period of time and then accessing and analyzing the data. The data processing would have been challenging if these studies had taken place 10 or 20 years prior due to the obvious raw data. However, with the availability of AI and ML technologies, processing large volumes of raw data has become simple and takes much less time. So, nowadays, any experiment that is conducted on almost any topic involves ML algorithms the outputs were to be gathered in less time and with more accuracy. The proposed method collects data by watching the fishes and their behaviors under various conditions that are introduced in the tank. These variables and behaviors are captured and saved using a camera. To gather data, we mounted the camera above a tank and watched it for 20 days, 24 hours at a time.

Process of the system:

- Experimental setup with the tank and fishes using a camera.
- YOLO Algorithm is used for Image Processing and Fish Detection
- Using a Deep Learning system, the data is collected and behavior is predicted.
- Statistics on Fish Behavior.

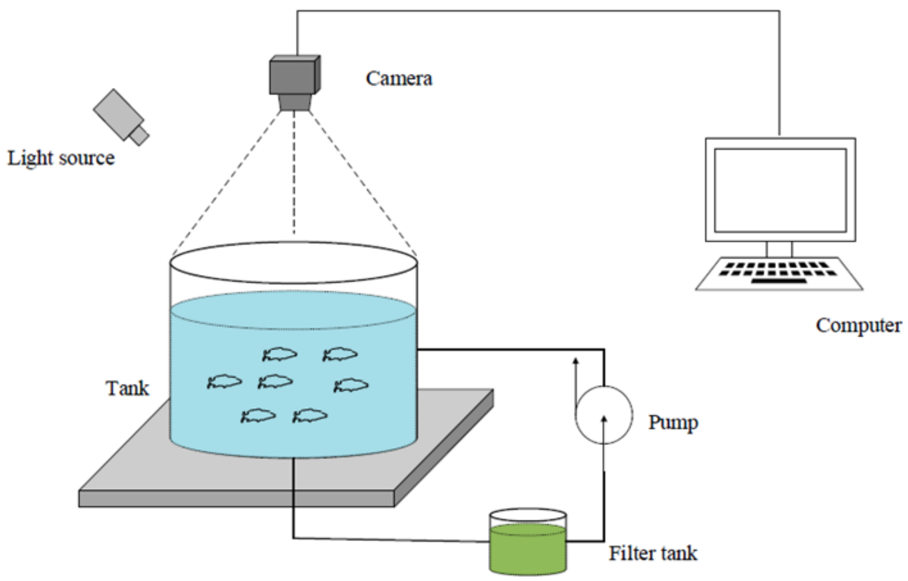

Fig 1 : Experimental setup of the proposed system

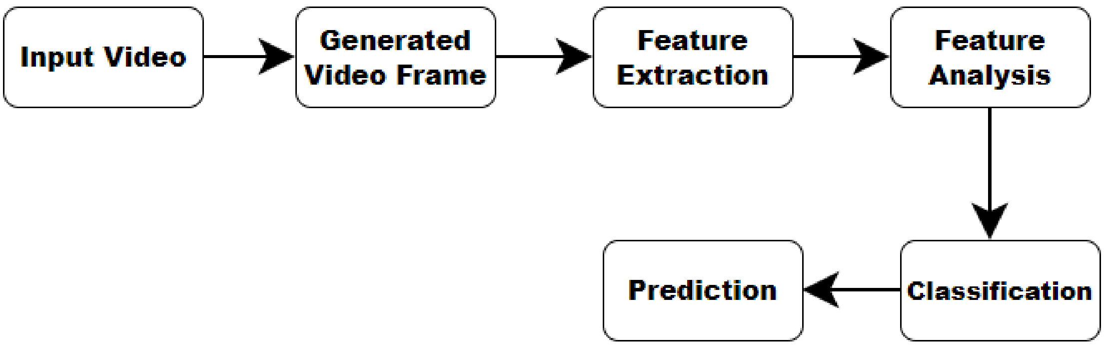

Fig 2: Basic Deep Learning Method

YOLO is implemented to detect fish with an absolute accuracy which was reasonable. This algorithm has been one of the explicit object detection methods, which estimates the classification of image and area of interests in a single encounter. It works by using a unique neural network to process the entire image. The network then splits the picture into segments and evaluates the probability of each segment. Instead of YOLOv2, the YOLOv3 algorithm is applied since it is an exceptional version with much more reliable results.

After recognizing the fishes and observing their behaviour, an evaluation is performed. The aggregated data collected during the pre-processing stage is used in the detection processof individual behaviour. To begin, the mean of all acquired data is determined. Next, the quantity of all black pixels out from masked picture of the paths are added, which aids in determining that whether the fish activity is accurate. Finally, multiple algorithms were evaluated to see if these attributes might be used to detect aberrant behaviour. The condition of movement direction and speed, in fact, are primarily reflected by the behavioural traits of fish.

To that purpose, FlowNet2 developed videos of optical flow for motion detection on RGB videos, it focuses on the fish's movement features, and the HSV image represents the direction of movement.

Behaviors	**Precision**	**Recall**	**Specificity**	**Accuracy**
Normal	98.5%	94.9%	99.6%	98.6%
Hypothermia	91%	96.8%	96.9%	96.9%
Hypoxia	97.8%	98.6%	99.4%	99.2%
Feeding	95.5%	89.2%	99%	97.2%
Frightening	97.8%	100%	99.6%	99.7%

Table 1 : Fish behavior prediction

The goal of our approach was to use optical flow to identify the movements of several entities in an RGB picture. To do this, we converted the existing C3D model into dual-stream system that accepts RGB and optical flow videos at the same time. The visual and mobility characteristics in feature fusion photographs give extra information of fish's movement.

Results and Discussion

The activity patterns of five fish groups indicated by distinct behaviours are included in our dataset. The typical accuracy of behavioural analysis is reported to be 94.5 percent for our suggested system's outcomes. Table shows the results of the model's accuracy, specificity, recall, and precision on five different fish behaviours. In regard to a minimal sample size considered, our recommended method allows for reliable assessment on fish behaviour. We chose 659 fish behavioural videos as the training case to assess the method's efficiency. Hypoxia and frightening behaviour, for example, had low recognition accuracy, with 95.9% and 96.2 %, accordingly.

On experimental dataset that was provided, we evaluated and analysed the most popular deep learning algorithms for detecting fish behaviour, including 3D residual networks, CNN-LSTM, and LeNet5 as shown in Table. LeNet5 is CNN-based algorithm for assessing fish feeding activity and demand by analysing visual aspects of feed intake. Furthermore, 3D-ResNet is indeed a deep CNN that collects information from videos in both spatial and temporal dimensions and has been used to recognise fish breeding and eating patterns. The CNN-LSTM model integrates CNN feature extraction with the time series learning capacity of a RNN (Recurrent Neural Network), which has been used to recognize animal behaviour.

We used the C3D network to directly extract the spatio - temporal features in RGB dataset as well as the motion characteristics in datasets of optical flow, and we achieved feature fusion in last layer of extracting features, inspired by dual-stream system. The algorithm's accuracy rate is 2.46 percent greater than CNN-LSTM and 6.97 percent higher than standard 3D residual networks, according to the research.

We discovered that using a 3D convolutional network with data augmentation as feature extractor is better for classifying fish behaviour.

Methods	**Accuracy**
LeNet5	87.06%
3D residual networks	88.82%
CNN-LSTM	93.33%
Proposed framework	95.79%

Table 2 : Accuracy level for fish behavior

Conclusion and Future work

Throughout aquatic ecosystems, the behavioural detection is crucial for risk analysis. Advanced CV algorithms can be used to measure precise individual behaviours and physiological states. Occlusion is by far the most common stumbling block in the lives of many individual studies. To increase the detection accuracy of a significant number of fishes, sophisticated algorithms are being developed to extract precise biological features of fishes. The five behavioural stages of the fish population, including feeding, hypoxia, hypothermia, frightened, and normal behaviour, are accurately detected using this method. This algorithm's accuracy rate for detecting fish behaviour has achieved 95.79 percent. On the testing dataset, it clearly demonstrates the efficacy of our technique. The RGB camera we employed in our technique may be used in real-world farming, which really is beneficial for everyday maintenance.

In future studies, we will be able to anticipate the hazardous levels of water and fish ingested, and we will be able to incorporate this information to estimate good fish for aquaculture and the marine ecology. We can aid both fishes and the marine ecology by anticipating hazardous levels, allowing concerned parties to start cleaning up the seas and water and implement the appropriate actions. Toxicity detection based on video monitoring, on the other hand, is still in its inception. To enhance toxicity sensing systems to be used in real-world applications, a number of challenges must be addressed. Recent tracking techniques, for instance, demonstrated exceptional proficiency in tracking a set of fishes through occlusions. However, these technologies are computationally intensive and, at this moment, are unable to generate actual information enabling online monitoring. Standard methods for evaluating behavioural activity must be designed for toxicity assessment.

Furthermore, 3D behavioural analysis of the data, which might give more comprehensive patterns of behaviour, has still not been frequently used. More research is needed to develop behavioural-based marine monitoring and to investigate the relationship amongst aquatic organism behaviour and environment.

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