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ORIGINAL RESEARCH

YOLO fish detection with Euclidean tracking in fish farms

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Abstract

The activities of managing fish farms, like fish ponds surveillance , are one of the tough and costly fish farmers' missions. Generally, these activities are done manually, wasting time and money for fish farmers. A method is introduced in this paper which improves fish detection and fish trajectories where the water conditions is challenging. Image Enhancement algorithm is used at first to improve unclear images. Object Detection algorithm is then used on the enhanced images to detect fish. In the end, features like fish count and trajectories are extracted from the coordinates of the detected objects. Our method aims for better fish tracking and detection over fish ponds in fish farms.

Keywords Image enhancement · Object detection · Object tracking · Fish farming

1 Introduction

Throughout time fishing has evolved in multiple ways until humans reached the idea of growing their own fish and that was the birth of fish farms (FAO 2017). Fish Farms have become important in the modern life as they have a huge contribution to the economy and ensures a reliable supply and wide distribution of fish all over the world. Fish farming is a costly and tedious process that requires a lot of labor work, more than 67% of the cost of a fish farm goes to labor work (FAO 2016). In 2017, the top ten countries produced 71.2 million tonnes of fish, they made up 88.9% of the global fish production (Bank 2014). Fish provides more than half the population with at least 15% of their average consumption of animal protein per capita (Béné et al. 2015). Also, since 1950, the global fish supply has multiplied 8 times (Béné et al. 2015). Case studies were done in several countries to calculate the production value of aquaculture industry (Phillips et al. 2016). The total aquaculture production value of these countries was around USD 71 million farm gate value, which is the difference between the market value and selling costs (transport and marketing costs), which stands for 72% of the global aquaculture production value (Phillips et al. 2016).

Our system aims to provide an efficient technique that detects fish and their trajectories, which in turn reduces costs spent on the manually done tasks by the fish farmers and aid them with a solution to their time/labor-intensive tasks, like manually analyzing fish trajectories (Beyan et al. 2012; Papadakis et al. 2012) to help them focus on their fish production.

There are many tasks that happen in a fish pond that requires constant monitoring of the ponds by farm-workers. These tasks are done manually like the known traditional processes done by fish farmers or automatically like the work done by (Lumauag and Nava 2018; Spampinato et al. 2010; Fier et al. 2014; Rodriguez et al. 2015; Long 2019; Alamiedy et al. 2019) and by Microsoft and Gramener (Microsoft and Gramener 2019), where they used deep learning AI models with the aid of infrared sensors to detect fish species. As mentioned before, the labor costs of controlling the fish farm is high so, detecting these tasks automatically would lower the high labor costs for fish farms. For example, these tasks are related to regular fish counting and detecting fish trajectories (Beyan et al. 2012; Papadakis et al. 2012).

Different tasks like disease control, fish feeding and detecting anomalies in ponds are done by fish farmers in

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order to control their fish farm. Those tasks require constant and long hours of monitoring from fish farmers (Lumauag and Nava 2018) which may lead to some problems due to the human-error factor (Lumauag and Nava 2018; Pandit and Rangole 2014). Fish counting and tracking is also challenging due to the movement speed of fish underwater and their overlapping (Lumauag and Nava 2018). Also, the variation in water condition and quality makes counting even more complicated (Lumauag and Nava 2018; Sharif et al. 2015).

Lack of monitoring leads to fish loss (Holmer et al. 2007) so, monitoring the fish farm automatically would lower the risks of fish loss. Some fish behaviors indicate their need of something regarding their health, like when fish swims upwards till the top of water indicates their need of oxygen (Kramer 1987). Oxygen is critical attribute for fish that helps them for respiration (Dong et al. 2011). Overcrowded fish ponds have less oxygen levels due increased fish activity and respiration (Svobodová et al. 1993). Therefore, detecting how many fish are in a pond helps fish farmers to maintain oxygen levels per each pond.

To avoid relying on manual methods for monitoring a farm, our system will utilize image processing techniques to accurately address any issues in a pond. Video footage analysis of fish in many similar systems was performed underwater in seas/oceans (Fier et al. 2014; Boom et al. 2012) or in controlled environments (Lumauag and Nava 2018; Rodriguez et al. 2015; Morais et al. 2005), where the visual quality was better than in a fish farm pond.

In this paper, we provide a fish farm monitoring system that is based on a combination of algorithms to detect fish count and trajectories. Firstly, we enhance turbid underwater images by Multi-scale Retinex algorithm (Petro et al. 2014) which makes it easier for further steps. Then, we use the YOLO (Farhadi and Redmon 2018) trained model which is trained by our own dataset to detect fish count. Finally, we get fish trajectories by combining the YOLO object detection and optical flow algorithm to track fish movements by each frame in the video.

This paper is constructed in the following way. Section 2 provides our related work in this domain. Section 3 describes the methodology of our system. Section 4 shows the experiments and results that were done and obtained. Finally, we summarize the paper in Sect. 5.

2 Related work

In this section, we explain the literature review that is concerned with the same domain. Our related work is divided into two sections. One for explaining the fish detection and tracking and the other for image enhancement underwater. Many methods and algorithms are introduced regarding underwater image enhancement and fish size, count and trajectories.

2.1 Fish detection and tracking

Various methods have been done to detect fish in order to track their count and size. For detection of fish different object detection algorithms have been applied (Duggal et al. 2017; Lumauag and Nava 2018). To track fish size and count image processing and computer vision systems are considered (Lumauag and Nava 2018; Toh et al. 2009), (Rodriguez et al. 2015; Boom et al. 2012). In order to track fish movement, tracking algorithms like optical flow and frame subtraction are done (Chen et al. 2011; Nguyen et al. 2015).

Duggal et al. (2017) wanted to create a model that automatically describe the video through object detection algorithms. Explanation of a video content is an easy task for a human being to do, but it is a complicated and difficult task for computers. They used the YOLO object detection algorithm as a base for the proposed system. Their proposed model gives better results compared to the other two models as it's faster and got less memory overhead. They used YOLO object detection algorithm which will be used by us to detect and count fish.

Lumauag and Nava (2018) motivation was to rely on computer vision to count fish as manual counting is a difficult process. The problem with manual fish counting is that it consumes much time and causes eye fatigue. The researchers used image processing techniques (blog analysis and euclidean filtering) to automate the process of counting fish. The system sometimes had issues with over-counting and/or under-counting. Over counting was caused due to lighting conditions. Their stated accuracy was 94% for successful detection and 91% for successful counting. The paper is useful as a good basis for counting fish from the same camera position that we are going to use.

Toh et al. (2009) wanted to automate counting fish in a pond to help giving accurate feeding as counting fish for humans is time-consuming and is subjected to errors. They found an easy method with high accuracy and less computational complexity that count fish. Firstly, they used the background estimation technique to obtain the initial blob. Then, they remove the noise from the image. After that, the remaining blobs are only fish so to detect a single fish they used median area of all blobs. Out of 30 frames, only one frame got an error in counting of 2 excess fish. This paper inspires the idea of fish counting and gives some specific details as background estimation and background subtraction to improve images to get accurate fish count.

Rodriguez et al. (2015) have done this paper to study biological changes on fish such as size change based on a stereo system using an image processing algorithm. Their main problem was getting an accurate estimation of fish size in the pond as it may indicate many factors in fish. Firstly, They detected the fish by using the distance map obtained by the stereo-vision system using an image processing algorithm. Then, they estimate the size of the fish by a segmentation technique to detect fish in the region of the RGB space corresponding to the location in the disparity map. They got only 10% error rate in estimating fish size and 90% precision rate. This paper helps us in detecting fish size by providing fish detection techniques based on stereo-vision system and segmentation algorithms so we get an accurate fish size estimation.

Boom et al. (2012) aim to study the effects that climate change and pollution has on the environment. Long-term monitoring of the underwater environment is labor-intensive work and other ways of data collection are also labor-intensive. They offered a system that detects and tracks fishes then recognizes the fish using its color and other attributes. Their system is still not fully functional, but so far their system shows a detection and tracking rate of 79.8% with an 11.8% false detection rate. This paper is useful to us as it introduces the idea of covariance based fish tracking, along with multiple background subtraction methods to improve our fish detection.

Chen et al. (2011) propose a new method based on optical flow to track any moving object. It's always tough to track an object's contour in complicated scenes. Firstly, they use an algorithm to get the velocity vector. Then, they get the object's contour by getting the position of moving pixels between frames. Finally, they calculate the position of the object and speed by using the position values. Their results showed accurate tracking of objects while the camera is motionless. This paper helps us to track fish movements by providing an optical flow algorithm that is based on calculating position and velocity of the moving object.

Nguyen et al. (2015) provide an algorithm to improve the tracking of fish movement. Their problems in tracking fish were showing an illusion of a fish, motionless fish and fish moving at different speeds at different times. They proposed a method that solve all these cases by combining frame difference and Gaussian mixture algorithms. Their proposed algorithm gives better results compared to the other 4 algorithms as it tracks fish in different cases. This paper is helpful to our research as it explores the use of Gaussian Mixture Model in background estimation to detect the fish at a high accuracy in low water quality, while also introducing the use of Kalman Filter to track the detected fish at a high accuracy in difficult conditions.

2.2 Water impurification

In order to get better results in tracking and detection of fish, we enhance unclear underwater images in fish ponds (Tang et al. 2019; Lu 2013).

Tang et al. (2019) proposed a system that enhances turbid underwater images to get a nearly natural color of the image. Their primary issue was that pictures and videos are generally rather poor in marine settings with a non-uniform illumination, color degradation and low contrast due to the marine environment. They proposed an image enhancement method based on Retinex algorithm which enhances images under different underwater conditions. They compared their algorithms with other 4 enhancing algorithms and found out that their method is better and faster than other algorithms in most of the cases. This paper introduces the Multi-Scale Retinex algorithm which will be used by us to enhance unclear underwater images to get better results in detecting fish.

Lu (2013) wanted to create a new and fast algorithm to enhance images underwater by reducing noise level and improving global contrast. Taking images underwater is challenging as it always suffers from light distortion and scattering. They proposed a model consisting of trigonometric bilateral filters which are responsible for noise removal and edge-preserving and α ACE-based technique that colors the distorted images. They compared their model with other models and found out that their model gives better results than others with better computational complexity. This paper is useful for our fish detection accuracy as it introduces an enhanced and quick color correction method named αACE, which is an enhanced version of the method based on the ACE model that takes a long time in processing.

Our contribution is a new technique that enhances object detection in unclear water environments with the help of color correction, and this technique is then used to further improve trajectory tracking precision.

3 Methodology

In this section, Our method (MSR-YOLO) is explained in detail. In order to get better fish detection our algorithm integrates the Multi-Scale Retinex (MSR) (Petro et al. 2014) color enhancement algorithm with the YOLO algorithm. After detecting fish, they are tracked to extract features like fish trajectories. Finally, fish trajectories are combined with YOLO to get the different fish movements.

3.1 Pre-processing

The key aim of this process is to get improved fish detection. The algorithm for improving unclear water images is presented here.

3.1.1 Image enhancement

It is useful to enhance the images/videos in our system since this make ambiguous water images/videos more clear. To do so, we use the MSR algorithm (multi-scale retinex) (Petro et al. 2014). Land and McCann were the first people to design the concept of Retinex (Land and McCann 1971). This technique follows the following steps. First of all, the image is passed through the Single-Scale Retinex (SSR) where the image logarithm is subtracted from its' Gaussian Filter. The equation below shows the first step,

$$R(c, d) = log(I(c, d)) - log(F(c, d, \alpha) \times I(c, d)) \tag{1}$$

The original image is represented as I(c, d) and Gaussian Filter Image is represented as F(c, d, α). The second and final step is when the image proceeds to Multi-Scale Retinex (MSR) where it outputs better results for enhancing image. This step is also shown in the equation below.

$$R(MSR) = \sum_{I=1}^{I} (log(I(c, d)) - log(F(c, d, \alpha) \times I(c, d))) \tag{2}$$

The improved picture is represented as R(MSR) and I is the scale numbers in the MSR.

3.2 Processing

The system then processes the data after finishing the pre-processing phase. Detecting Fish is the first process that is done by using YOLO algorithm (Farhadi and Redmon 2018). Fish are then tracked to finally, combine fish trajectories with YOLO so we get each detected fish movement.

3.2.1 Object detection

The algorithm used to detect objects is regression-based algorithm. In one run for the algorithm, YOLO calculates the region of interests and classes for the image (Redmon et al. 2016). Firstly, one neural network is processed on the entire image. The image is then divided into different cells and the objects are predicted in each cell. The algorithm surpasses peers (e.g: RCNN, Faster RCNN) as it configures a global image context view (Farhadi and Redmon 2018). Moreover, for prediction of the object in a single image, it takes YOLO one neural network while RCNN consumes a large number of neural networks (reaches to thousands) (Farhadi and Redmon 2018). In building our method, YOLOv3 was used instead of YOLOv2 as it is an upgraded version which produces more faster and accurate outputs (Farhadi and Redmon 2018).

To create our model, 2000 images of golden fish were captured. Then, to label the fish (our region of interest), labeling software was used that provides the coordinates of each labeled object by writing these coordinates in a text file for each image. After that, In training our model, it took 9000 epochs to reach the end of training since the average loss percentage was nearly the same for 2000 epochs. YOLO tiny weights was used to train the dataset (images and the text files) over the YOLO weights since it was designed for the usage of only one class which is our case and it is smaller and lighter version yolov3weights which is designed for larger number of classes.

3.2.2 Fish tracking

YOLO object detection does not hold and treat objects as the same in each video frame. So, each fish detected across video frames is assigned a specific label/ID. Murugavel used this algorithm on humans (Murugavel 2019) which will be applied on fish here. It is essential to use fish tracking as it will be beneficial in further steps. Tracking fish algorithm takes each detected fish center points in each frame which is delivered to an array, where the coordinates of the last 8 frames are stored. Then, distance is measured (euclidean distance) between the fish current coordinates and previous frames coordinates. The detected fish is either given a new id or remains with its same id in previous frame. The fish gets its' last stored id if the measured distance was less than 50 pixels. While, if the distance was more than 50 then the fish gets a new id. The tracking method is visualized in Fig. 1.

Two empirical studies were conducted in order to figure out the numbers chosen for number of frames to be tracked (8) and minimum distance to calculate distance between fish (50). Firstly, the 8-frames has been chosen because the fish will not move far over 8 frames, so by choosing 8 frames we can obtain enough positional data to calculate the minimum distance of the unidentified fish. Secondly, The 50 was chosen as the minimum distance as a threshold value because when testing with larger numbers than 50 it gives different fish the same label/id. Also, when testing with lower numbers than 50, same fish would be given the same id over different video frames.

3.2.3 YOLO and trajectories extraction combination

The tracking part plays an important role in this phase as the trajectories that are drawn for each fish depends on it. A line is drawn between the referenced point and current point of the fish that have the same id. Also, a circle was drawn to determine the middle point of each fish.

This method was combined with our trained model. First of all, YOLO gives the top left point of each detected box. After that, those values are then divided by two to calculate the center x and center y of the box. Lastly, the center coordinates calculated are given to the trajectories method to draw fish trajectories.

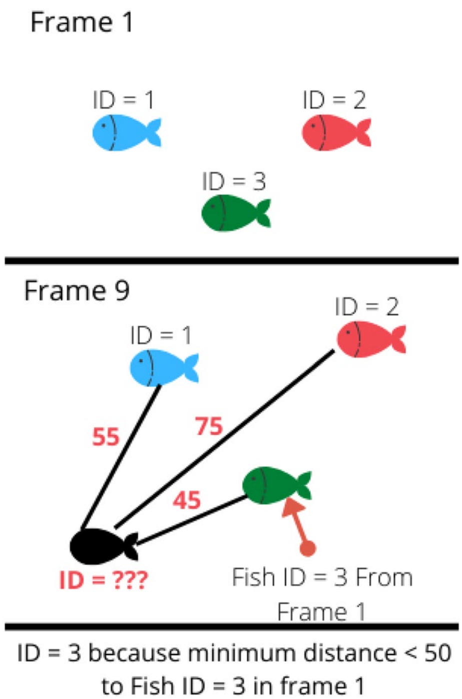

Fig. 1 Calculation of each fish nearest distance

4 Experimental results

Our experiment setup is presented in this section firstly. Then, the dataset used and collected is explained. In the end, two experiments are conducted and their results are shown.

4.1 Experiment setup

The fish tank built in controlled environment that is based on the guidance of the Suez Canal University Fish Research Center so we can test our algorithm. A temporary fish tank of 60 liters, 100 cms length, 40 cms width and 35 cms height was brought to do tests on it. In the morning the fish tank was under normal sunshine, while in the night it was under average room light where it was monitored at ordinary temperature. Web Camera was put above the fish tank so we can capture videos and images. For running out method tests and processing our model, a 16 GB RAM and Intel Core i7-6700HQ CPU 2.60 GHz laptop was used. Also, Google Colab was applied to increase the performance. The setup and its' components is shown in Fig. 2.

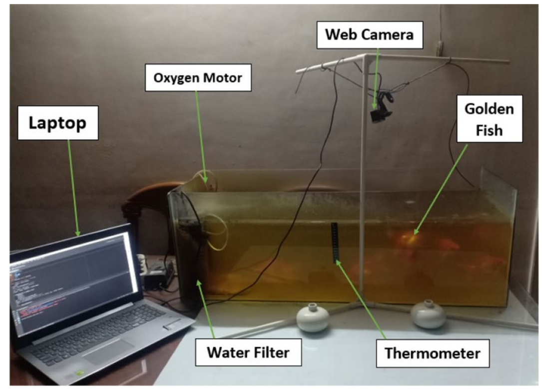

Fig. 2 Experiment setup

4.2 Dataset

A dataset was made for the YOLO model to detect fish. It contained 2000 images of golden fish that were collected from our setup.

4.3 Experiment 1

4.3.1 Objective

The main idea of this experiment is to enhance unclear images of water. The water was healthy and clean but was unclear. This experiment also allows us to decide the best location to put the camera according to the pond. The accuracy was measured before and after the enhancement algorithm was applied. 30 images were tested from the two different situations applied (underwater or above) so we can get the average detection of our model.

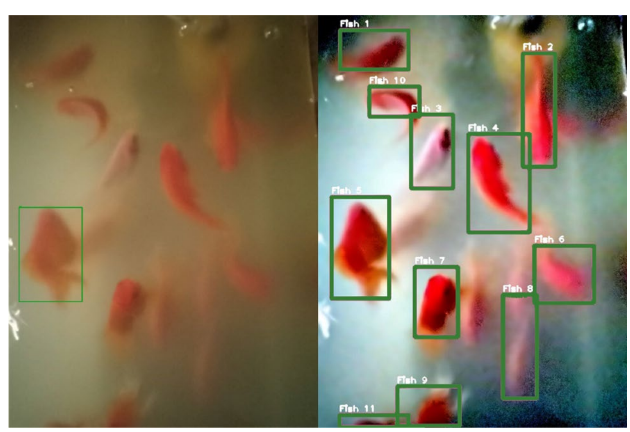

Fig. 3 Above the pond image, left: before enhancement, right: after enhancement

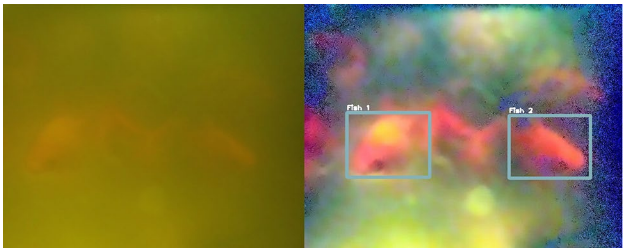

Fig. 4 Underwater image, left: before enhancement, right: after enhancement

4.3.2 Results

As mentioned previously, two kinds of images were taken to run tests on the enhancement algorithm. Images where the camera was settled above pond as in Fig. 3 and images where the camera was settled underwater as shown in Fig. 4.

The model showed that 3 fish can be detected from above and 1 fish can be detected from underwater on average while the images were before enhancement. These numbers are shown in the left graph in Fig. 5.

The model showed better outcomes after enhancement as it detected 11 fish from above while, it detected 2 fish from underwater on average. These numbers are shown in the right graph in Fig. 5.

So, Firstly, there was no significant change in the underwater images detection before or after enhancement. So, the camera was settled above the pond. Also, Fish tend to swim close to surface so, it does not affect their behaviors. Secondly, images after enhancement are better in both situations which solidifies the idea of using the enhancement algorithm to enhance detection accuracy.

4.4 Experiment 2

4.4.1 Objective

The aim of this experiment is to compare between the performance of two methods that are used to draw fish trajectories and track their movements. Firstly, we used combination of YOLO and optical flow as in our previous work (Mohamed et al. 2020) and compared it with the trajectories method explained before in methodology section.

4.4.2 Results

The two methods tracked all fish detected by YOLO due to the combination done with it. The trajectories extraction method shown to be better than optical flow method as it produced more accurate trajectories.

To illustrate visually, the trajectory lines drawn in Fig. 6a shows the optical flow drawn trajectories which lacks accuracy due to the scattered lines and wrong drawn lines of

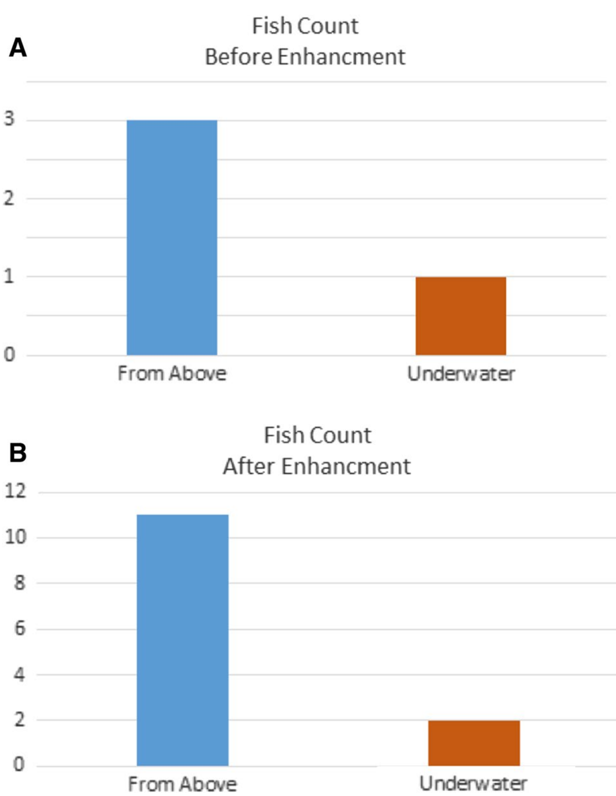

Fig. 5 Fish count average graph (based on 30 test images). **a** Before enhancement. **b** After enhancement

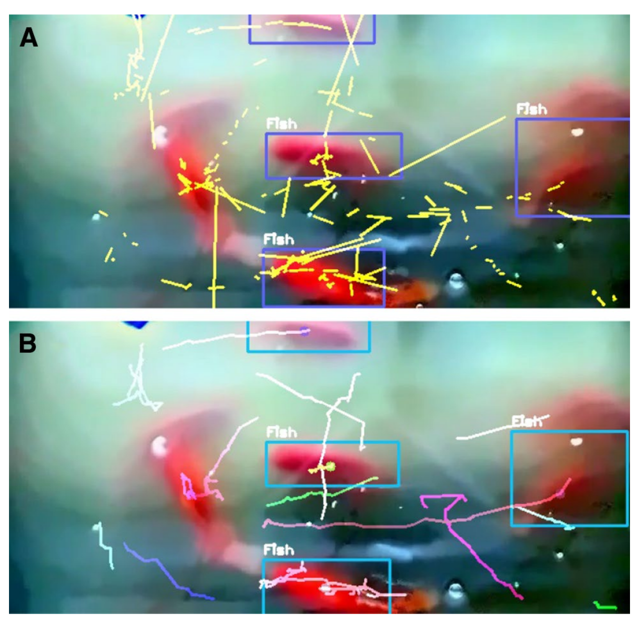

Fig. 6 **a** Optical flow and YOLO combination. **b** Trajectories extracting and YOLO combination

fish movements. While, Fig. 6b shows the trajectories drawn using the tracking method and yolo gives better results as it draws each line without scattering and tracks every detected fish. Moreover, the trajectories extraction method reduces the overhead that was done by using the optical flow method.

5 Conclusion and future work

In this paper, we combined an enhancement algorithm based on retinex (MSR) with an object detection algorithm (YOLO). This method shown to detect fish better in unclear water which can help with detection of many different features in fish farms.

In the future, clustering should be used especially unlabeled type which can detect and cluster many different behaviors of fish in fish ponds of fish farms through extracting different features of each fish in the ponds.

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