Species Detection Of Fish, Tracking And Weight Monitoring System Using Machine Learning

Shraddha Sangewar[1*],Somulu Gugulothu[2]

Abstract
Our suggested model will demonstrate processing methods for fish identification and tracking automatically from video sequences. In particular, fish farming operations and global environmental protection call for substantial research on this topic. Both nature protection and the food business benefit from the computerized monitoring and counting of various fish species. Fish farms are likely to raise subpar fish to meet the increased food demand brought on by the world's expanding population. Monitoring fish growth has a significant influence on the industry that produces aquatic animal food since it helps produce fish products of higher quality. This model will feature a continuous autofocus, surveillance, and mass prediction system based on cost-effective monitoring techniques for several fish species. Instead of utilising the conventional way of taking measurements of the fish, this study uses image analysis to track fish growth in an effort to increase fish growth rates.

Keywords—Computer vision, motion detection, background sub-traction, tracking, Yolo.

[1*]Asst.Professor, Dept. of IT, YCCE, Contactno: 7709387714, Nagpur, India, Email: shraddha26sangewar@gmail.com
[2]Software Developer, Incedo Technologies, , Contact no: 9021235561, Hyderabad,India, Email: gugulothusomulu06@gmail.com

***Corresponding Author:** Shraddha Sangewar
*Asst.Professor, Dept. of IT, YCCE, Contactno: 7709387714, Nagpur, India, Email: shraddha26sangewar@gmail.com

I. INTRODUCTION

It is impossible to exaggerate overall value of marine habitats and fishery commodities. In order to safeguard and utilise marine resources, many scientists keep an eye on alterations in fish species and their habitats [1].Changes in species, for example, can be used as indicators of climate change in specific regions. The Underwater Optical Sight provides the most comprehensive underwater acquisition information. Automated optical fish identification can help researchers better understand marine echo systems. A portion of the entire scene. The visual quality of the video sequence, which was captured with a professional camera, is noticeably superior. For the video, detection and tracking techniques were used to evaluate the effects of the video sequence quality. We also suggest an algorithmic method for locating fish in subpar video clips.

II. LITERATURE REVIEW

Recent studies [3], [4] use deep neural networks to classify fish into different species. In order to process the characteristics gathered from a fish image, [4] uses a multi-layer learning algorithm as a classifier. These traits are based on data that are well-known, such the size and shape of the fish. Modern Convolutional Neural Networks (CNNs) are employed in [3] as both a feature extractor from an input image and a classifier of these recovered features. [5-7] present strategies for identifying and detecting fish in photos, as well as for categorising the found fish into the appropriate species.

The research in [5-7] is based on a well-known but substantial design called Faster R-CNN [8]. This model is at present one of the most efficient in terms of entity detecting precision. The majority of reference tools for underwater fish classification and identification are designed for non-intrusive settings, with the surveillance system installed in a defined location. Most of the data offered in these articles is often of good quality and includes information on underwater conditions, contrast, and visibility. The main goals for classifying species are based on a large-scale fish dataset that is already accessible, such as G. [9], which largely includes high-quality photos of tropical types of fish and neglects to pay attention to species chosen outside of this range.

Such computerized fish identifying and categorizing systems typically have poor scalability and dependability. Traditional image processing faces difficulties when it is exposed to unfamiliar surroundings, noise, and less-than-ideal conditions since it typically does not extend outside of the area that it was developed. The impacts of these fluctuations in the data are attempted to be eliminated by models built on a lot of data, although this is usually the case.

III. PROPOSED METHOD

A. Implementation of YOLO Network.

Therefore, we suggested a CNN-based fish detection method. The conventional method of object detection matches reduced properties, such as a defined outline form and a colour pattern. However, due to poor lighting, high levels of noise, and image blur, this method did not perform well in underwater imaging. A CNN, on the other hand, uses a layered architecture to learn high-level functions and the classifier that uses those functions simultaneously.

The increased procedures learned in this scenario are particular towards the training data, therefore when put to the test, they are probably going to perform better than the low-level, generic functions. Using CNN, numerous entity classifiers have been created in recent years. The main goals of the study are to increase computational accuracy and speed. The increased procedures learned in this scenario are particular towards the training data, therefore when put to the test, they are probably going to perform better than the low-level, generic functions. Using CNN, numerous entity classifiers have been created in recent years. The main goals of the study are to increase computational accuracy and speed. In order to increase processing performance for real-time applications, several object detection techniques have been created.

B. Conversion of Dataset

We collected 320x240 or 640x480 resolution fish pictures. There are three types of fish in these images. Furthermore, some of the images are of poor quality. Some fish that are similar in colour to the bottom may be seen, and there may be a collision between the fishes. We kept these lower images because unsatisfactory frames are common in underwater environments and due to equipment failures, and our goal is to build a strong and robust network for difficult marine environments.

The network receives these feature maps. The final feature maps' features are weighted by the fully linked layer to create a probabilistic model over all conceivable classes. The network model is tuned using a variety of hyperparameters, including input picture size, learning rate, the quantity of convolutional layers, the amount of layers in each convolution operation, and error correction techniques.

Fig. 1 Dataset image

C. Balancing the new fish data set

We omit fish classes whose recurrence times are fewer than 600 because, as was already noted, a number of the fish classifications are not quantitatively balanced.

D. Modifying the Basic Reality of Fish

In our new dataset, the descriptions for every Image video were transformed into descriptions for each image. The same fish class may have two alternative spellings, and some object values may be negative or beyond the resolution range. These are examples of noisy markings on fish categories and bounding box values. We manually altered these erroneous annotations in order to deploy Fast R-CNN toward the new fish given dataset.

E. Training.

Data extension, a convolutional network, as well as a fully - connected layer at the very end of the pipeline, which is combined with a linear kernel, make up the training phase. This design's individual elements each have a distinct function. The main purpose of convolution layers is to retrieve image features. A predetermined number of filters are present in each convolutional layer. These filters, which are weighted kernels, are applied to the image to produce the required feature maps.

F. Measuring Bass weight of the fish:

The bass weight of fish of the following species are calculated by using the formula :

(l×l×g)/1200

Where l-length of fish

g-girth of fish

For example , if the fish is 22 inches(56cm) long and it has a

girth of 10 inches (25cm) , the formula would look like :

(10 × 10 × 22)/1200=1.83lb

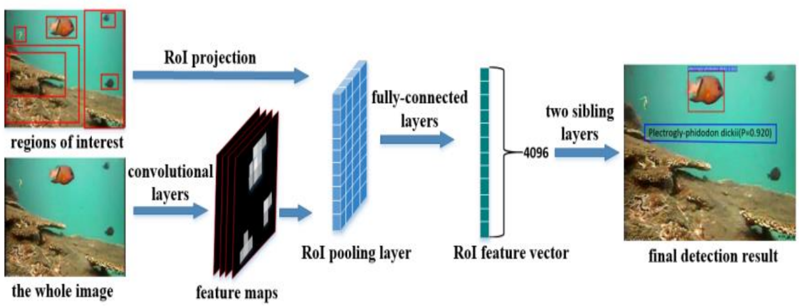

Fig 2: Proposed Implementation process

IV. RESULT

A. Training result

As the number of species of fishes in our dataset is limited , we have taken each fish in a frame multiple times. A total of 200 fishes were present in our dataset of 3 species (i.e. katla , tilapia and Cmangur)

B. Object detection result

We tested the neural network with a collection of 200 fish videos after programming it. As seen in Fig. 3 below, the neural network recognises fish and provides connected components around the fish has found..

Fig.3- Screenshot of video taken for analysis for analyzing weight and age of fish

V. CONCLUSION

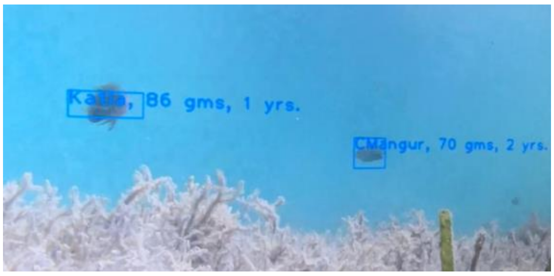

Fig. 4: Calculation of weight and age of other fishs in the video

The research proposed the drafting algorithm for detecting, localising, and categorising fish and fish species in murky water environments. We employ YOLO's architecture for real-time detection and train the network using unique fish photos. This made it possible for us to quickly identify fish. A neural network is developed on numerous photographs of the target to recognise it.

Since fish have insulating colouring on their bodies, many instances involving fish recognition have been mistaken for seafloor. It was important to train the network using randomly cropped seafloor photos in order to increase accuracy. To help marine biologists estimate fish populations and quantities and better comprehend the geographic and biological surroundings of the ocean, these intriguing connections are deployed to the computerized fish identification system..

VI. REFRENCES

1. Angermeier, Paul L., and James R. Karr. "Relationships between woody debris and fish habitat in a small warmwater stream." Transactions of the American Fisheries society 113.6, 1984, pp.716-726.
2. Gordon, Howard R. "Can the LambertBeer law be applied to the diffuse attenuation coefficient of ocean water?." Limnology and Oceanography 34.8, 1989, pp.1389-1409.
3. Xie, Yunbo, George Cronkite, and Timothy James Mulligan. "splitbeam echosounder perspective on migratory salmon in the Fraser River." (1997)
4. J. Deng, A. Berg, S. Satheesh, H. Su, A. Khosla, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Competition 2012 (ILSVRC2012).http://www.image-net.org/challenges/LSVRC/2 012/.
5. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A large-scale hierarchic- al image database. In CVPR, 2009.
6. H. Qin, Y. Peng, and X. L. Foreground Extraction of Underwater Videos via Sparse and Low-Rank Matrix Decomposition. Computer Vision for Analysis of Underwater Imagery (CVAUI), 2014 ICPR Workshop on. IEEE, 2014.
7. X. Li, M. Shang, J. Hao, and Z. Yang, “Accelerating fish detection and recognition by sharing cnns with objectness learning,” in OCEANS 2016 - Shanghai, April 2016, pp. 1–5.
8. S. Ren, K. He, R. B. Girshick, and J. Sun, “Faster RCNN: towards real-time object detection with region proposal networks,” CoRR, vol. abs/1506.01497, 2015. [Online].
9. A. Joly, H. Goeau, H. Glotin, C. Spampinato, P. Bonnet, W.-P. Vellinga, ¨ R. Planque, A. Rauber, S. Palazzo, B. Fisher, and H. M ´ uller, “Lifeclef ¨ 2015:

Multimedia life species identification challenges," in Experimental IR Meets Multilinguality, Multimodality, and Interaction, J. Mothe, J. Savoy, J. Kamps, K. Pinel-Sauvagnat, G. Jones, E. San Juan, L. Capellato, and N. Ferro, Eds. Cham: Springer International Publishing, 2015, pp. 462–483.

10. J. Huang, V. Rathod, C. Sun, M. Zhu, A. Korattikara, A. Fathi, I. Fischer, Z. Wojna, Y. Song, S. Guadarrama, and K. Murphy, "Speed/accuracy trade-offs for modern convolutional object detectors," CoRR, vol. abs/1611.10012, 2016. [Online].