# Dacia Sandero Project

## 1.Problem Statement

The problem that our team will be tackling is object detection in images, more specifically object detection in an underwater environment. By definition object detection is a technology related to computer vision that as the name implies handles the detection of objects belonging to a certain class (Object detection, 2020).The class of objects selected for this task is marine wildlife the reason for this selection being detailed further into the paper. With the selected environment comes with its specific set of challenges such as the ones identified by Xu and Matzner while tackling a similar problem, unequal spectral propagation, low contrast, different types of clutter and in certain cases unfavorable lighting.

## 2.Problem Motivation

The motivation behind the chosen problem when it comes to its possible applications in a real live environment comes from its possible us in ocean exploration and marine life monitorization. While the two stated reasons have completely different end goals there is also a noticeable overlap in the tools they employ and an object detection model that can perform well in underwater environments is something that can be used as part of the automation process in both fields. As mentioned by Ian Evans in his article Solving the Sky High cost of ocean exploration with A. I. the cost of operating an ocean research vessel for a day can range from 10.000$ to 40.000$ this cost representing a major constraint when it come to the further advancements of marine exploration and study. One of the proposed ways of cutting back on the cost is the use of automated research drones thus reducing the amount of manned vessels used for the different operations. Taking all this into considerations an object detection model that can perform reliably in underwater environments could play a crucial role in upcoming marine research projects.

## 3.Literature review

A relevant study of an underwater object detection model that can help with the development of our own project is detailed by Xu et al in 'Underwater fish detection using Deep Learning for Water Power Applications. The study in question due to the conditions in which the object detection model is deployed, as the title of suggests the underwater environments in which the fish are found is in close proximity to marine and river based hydroelectric plant this comes with a specific set of challenges such as the murky water the high turbidity and the high velocity of the objects. The study uses three datasets named Wells Dam, Voith Hydro and Igiugig  that have different recording qualities such as different resolutions, different

frames per second going from 10 fps to 30 fps, as well as different image coloration , with one of the datasets being grayscale. Another aspect of the datasets that needs to be mentioned is the diversity of fish species being monitored as well as the presence of multiple frames with no objects of interest. All this makes for a very robust dataset.
In terms of the model used they have selected YOLO version 3, YOLO is deep learning model with 106 convolutional layers used to detect a variety of different class, which was applied using the transfer learning method this allowed the team to use Yo1lo v3's weights in order to initialize the training.
The performance of the model was measured using the mean Average Precision, with the model scoring the best in the Wells Dam dataset having 0.5575 mAP and word on the Igiugig dataset with 0.4507 the lower performance being mostly due to false positives.
With all this taken into consideration this study is an important benchmark for working with difficult environments as it has a robust dataset and uses a state of the art open source model.

Another system detailed by Sampinato et all (2008) in his Detecting and counting fish in low quality unconstrained underwater videos meant to help with researchers monitor and classify marine wildlife, focused more on fish species is a good candidate for study due to its machine learning approach that does not include the use of a neural network. The system is divided in 3 different image processing systems.
The first being the texture and color analysis system which evaluates the following properties brightness smoothness and color which is first classified in green and not green with the later also taking into account the hue, saturation and value. The approach to describing the texture of each image is based on analyzing the grey-level histogram more precisely the statistical moments of each histogram.
For the Fish detection part of the processing system in order to complement each others shortcomings the system employs two algorithms one being the Adaptive Gaussian mixture Model which is used alongside a moving average algorithm which does not handle scenes where the background isn't static  to well but is better performing in terms of processing time and much easier to deploy, The gaussian model is used in order to reduce the false positives, also if used independently the model struggles with slow moving objects.
The third part of the system consists of the two algorithms used for tracking the objects one based on histogram matching and the other based on blob shape matching.
In terms of results the overall performance of the system was measured by its detection success rate and by the counting success rate with the detection rate varying from 81.5% to 89.5% based on the video sequence it was used in and the fish counting rate going from 75% to 92.5%. Due to the limited performance testing of the system only looking at successful detection and not taking into consideration precision along with this since the dataset used is not evaluated in the paper as well as it not being provided the applicability of system in multiple environments does not guarantee a good performance.

A more recent study that employed a hybrid between GMM, optical flow and Yolo v3. The datasets used for training and testing this model comes from LifeCLEF 2015 which is derived from the Fish4Knowladge repository as the first part of the set with the second part being collected by the research group at The University of Western Australia which has over 4418 videos of low visibility deep water instances of fish. GMM is an unsupervised machine learning algorithm that is used for background modeling, one disadvantage this algorithm has is that it requires pure background images without any fish present in the frame in order to train a background model to detect motion related features the lack of these conditions can sometime result in the miss detection of fish ,counting them as background objects. In order to address this downfall optical flow was used as an additional way of detecting motion related features as optical flow detects motion patterns generated by object in consecutive frames thus minimizing miss detection. The fish candidate are extracted by creating an hypothetical RGB image with the red and green channel being filled with blobs from GMM and optical flow and the blue channel being left black, the resulting image containing the regions of interest. Yolo v3 is incorporated in order to deal with the nonlinearity of the data that comes from changes in the light, the size shape and angle at which the fish is seen as well as the image quality and noise factors.

The performance of the models was determined by their F-score for both detection and classification with the proposed model the performance is as follows: Fish detection LCF- 15 95.47% UWA 91.2% and Fish classification LCF-15 91.64% UWA 79.8%. Another thing to note form the testing using yolo along both GMM and Optical flow alone yields results that are moderately close to the ones given by using all three together.

## 4. Project Statement

The aim of our project is to provide a robust object detection solution that can be deployed in an underwater environment with the aim of detecting marine wildlife, primarily fish. We aim to achieve this using open source datasets that can hopefully encompass most of the underwater environments where the model can be deployed. In terms of the usability the model is meant to be easily integrated into other systems and is not necessarily meant to be used as stand alone. When it comes to the architecture that the model will use to solve the problem a solution based on Deep learning seems to be the most efficient and as mentioned above  adapting a deep learning model such as YOLO v3 seems to be the most time effective way to proceed along with this access to resources such as google colab can be used to deal with our hardware shortcomings. To conclude our aim is to come up with an underwater object detection model using only open source and self created code and datasets.

# References

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