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優勝作品專輯

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參展科別	環境工程
作品名稱	Autonomous Ecosystem Surveillance Robot
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關鍵詞　Biosecurity, Biodiversity, Water pollution

作者照片



Abstract

Our project, the Autonomous Ecosystem Surveillance Robot, aims at closing the aquatic gap in biosecurity measures by including several functions, such as water quality monitoring, aquatic species monitoring, and seabed topology surveillance. Several instances have shown the need for such a system, as demonstrated below.

The United States Corps of Engineers completed an electrich fish barrier in the Chicago Sanitary and Ship Canal in 2002, in order to prevent the invasive Asian carp from moving into the Great Lakes. The introduction of the Asian carp into the Great Lakes would be an ecological disaster, as the Great Lakes provide an ideal habitat for the carp to proliferate, choking out native fish species that exist there. This would result in a major loss for the fishing industry in the area.

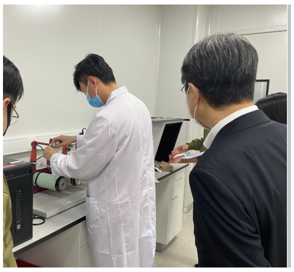
One of the Great Lakes, Lake Erie, suffers annual algae blooms threats, which affect up to 12 million people in the Great Lakes region of the United States and Canada. These algae blooms are caused by runoff pollution, which occurs when rainfall washes fertilizer and manure from farmland into Lake Erie, fueling algae that can make water toxic to humans and animals alike.

In addition, there are many existing customs regulations around the world that are set in place to ensure biosecurity of national ecosystems, such as in Taiwan, where it is illegal to bring pork from abroad. Despite this, there still exists a very large gap in biosecurity measures; that of the aquatic nature.

Through these three functions, we have the ability to protect local aquatic biodiversity via the ability to detect invasive species, therefore allowing authorities to properly deal with them. This allows less harmful measures to be taken against them, thereby limiting collateral damage to endangered native species. Coupled with the ability to map bodies of water, the Autonomous Ecosystem Surveillance Robot is an extremely potent tool to preserve aquatic biodiversity and to ensure biosecurity of local waters.

Background

A problem reservoirs commonly face is monitoring its water quality. As the source of drinking water for the citizens of its area, the safety of the water is of utmost importance to the governing body. Present methods of monitoring this growth of algae and nitrate rely mainly on laboratory testing water samples. These methods present two main disadvantages: **Inefficiency and delayed data.**

 -->  --> 

Manual sampling onshore.

Real time - chemist

To combat this problem, our team decided to create an all-round aquatic environment surveillance boat capable of surveilling prominent harmful factors regarding underwater ecosystems, being water quality, aquatic life, and water environment monitoring**.** This solution offers more autonomy and creates an overall solution to water body monitoring.

A. Water Quality Monitoring

Freshwater lakes such as Lake Erie in the USA and Lake Tai in China have been experiencing the emergence of "dead zones" caused by excess nitrate in the past decade. Nitrate promotes the growth of algae, during which the algae proliferate rapidly, forming dense populations. As the algae eventually die and decompose, bacteria and other microorganisms break down the organic matter, consuming dissolved oxygen in the process. The combination of increased microbial activity and the sheer biomass of the algae depletes oxygen levels in the water, resulting in adverse impacts on marine life, including fish mortality.

Noctiluca scintillans bloom. Coloane, Macau

Discharging untreated sewage cause pollution

Moreover, reservoirs, where algae commonly exist, are used to store drinking water, meaning that an algal bloom will have a detrimental effect on the citizens of the area. While there are methods of killing these algae in reservoirs, such as chemicals like algaecides, may be successful in eliminating algae and harmful substances, the usage of these chemicals will simply hinder the purification process of water, leading to a higher cost to produce drinking water.--引文

Algae bloom on the Sassafras River

For scientists to transport water samples back to laboratories for testing, a massive amount of time will be consumed, leading to inaccurate results as the aquatic environment is an ever-changing one. Furthermore, This method is unable to get data in real-time over an extended period of time, meaning that we are unable to accurately predict the possibility of an algal bloom accurately as the time differences between data is both inconsistent and too long.

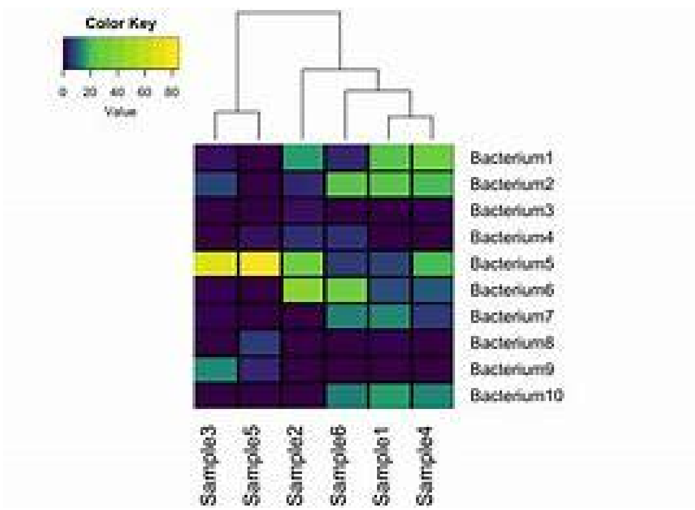
To address this environmental challenge, our team has developed an innovative boat capable of monitoring and predicting algal blooms in bodies of water. By leveraging the

Beer-Lambert Law and deep learning techniques, our boat analyses water samples to find nitrate levels. This enables the boat to provide valuable insight and predictions regarding the likelihood and potential locations of algal blooms, assisting in proactive management and mitigation efforts. Lastly, by applying regression models and combining weather data with the nitrate levels, the boat can predict and output a heatmap on the estimated locations for algal blooms to occur.

B. Aquatic Species Monitoring

Recognizing the additional threat posed by invasive species to water bodies, our team has also integrated a function within our boat to detect invasive species. Current methods to achieve this mainly rely on the human eye and passerby spotting to find invasive species in lakes or reservoirs, which is heavily unreliable, as passerby might not know who to contact or whether the fish is invasive.

To combat this, we created a system that employs advanced data analysis and pattern recognition and similarity comparison algorithms to identify the presence of invasive species in aquatic environments. By combining the frequencies at which an invasive species appears, we can output another heatmap of the species densities and estimate the population of the invasive species. This information can then be forwarded to a generative AI, which will then output advice to remove these species to officials.



Sample Heat Map

C. Water Environment Monitoring

Lastly, our team decided that litter detection would be the main aspect of research and usage in the water environment monitoring aspect. Traditional methods of detecting and removing litter from water bodies often rely on manual inspections, which can be time-consuming and inefficient.

Litter Detection Implementation On Land

Through the integration of data analysis and machine learning techniques, the on-boat computer can generate real-time maps or reports indicating the locations and densities of detected litter. This information can then be shared with relevant authorities and environmental organisations, enabling them to prioritise and efficiently allocate resources for litter removal and prevention efforts.

In summary, our all-round aquatic environment surveillance boat addresses the deteriorating water quality in lakes and reservoirs by monitoring and mitigating harmful factors such as nitrate levels, invasive species, and litter. By utilising advanced technologies like deep learning and data analysis, the on-boat computer predicts and detects algal blooms, identifies invasive species, and detects and maps litter in real-time. This enables proactive management and intervention efforts, leading to improved water quality, enhanced ecosystem preservation, and the protection of aquatic life.

Engineering Goals

Chemical treatments can have unintended consequences on the aquatic environment. Algaecides, for example, can harm not only the target algae but also other non-target organisms such as fish, invertebrates, and beneficial algae species. Similarly, the use of nitrate-reducing agents can alter the natural nitrogen cycle and disrupt the balance of the ecosystem.

Frequent and repeated use of chemical treatments can lead to the development of resistance in target organisms. Algae, for instance, can evolve and become resistant to certain algaecides over time. This can result in the need for stronger or more potent chemicals, leading to a continuous cycle of escalating chemical use.

In order to solve the problems stated above, our team decided to create a sampling system that is capable of collecting water samples from most depths. The aim of this project is to monitor bodies of water frequently via collecting water quality data from local reservoirs and to provide researchers and local authorities with swift and accurate water quality data to prevent disasters from happening. We have compiled a list of potential goals to develop:

1. Able to collect water quality data from most depths
2. Ability to be autonomous
3. Live water quality data (ph, dissolved oxygen, nutrients, metals, hydrocarbons, industrial chemicals)
4. Deep learning towards prediction of algae blooms
5. Conservation of biodiversity
6. Analyzation of underwater environment

Design

A. Hardware Design

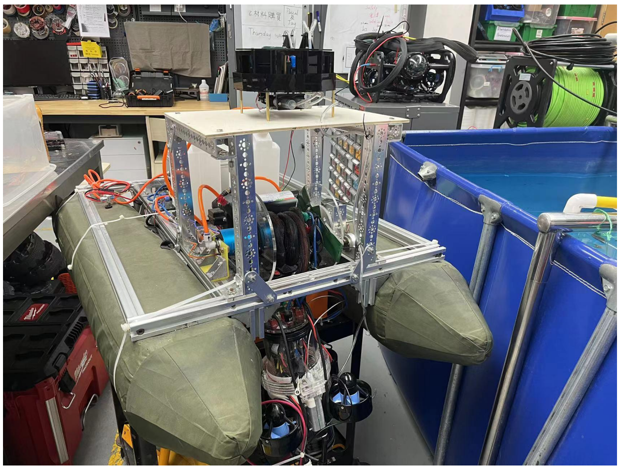
I. Generation One Design

In the beginning of the development of our boat, we created a prototype boat only capable of moving. As shown on the image below, the boat was only equipped with a computing unit on top. This design allowed the boat to be controlled wirelessly, but lacked other features such as a lowering platform for better data collection, a camera to monitor the ecosystems etc…

Initial design of the boat

II. Generation Two Design

After building the first design, we turned our hardware focus to specific task-related features. This included a lowering platform equipped with cameras to monitor the water at **different depths**, a new rotating platform for obtaining nitrate data on top, and a better battery system for the boat.



Second design of the boat

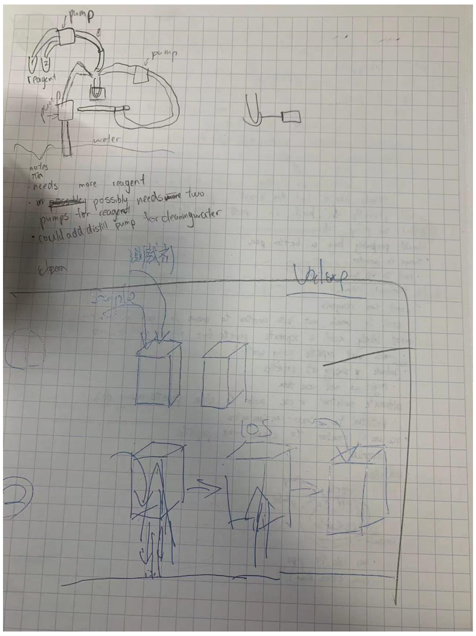
III. Sample holder

Collecting samples is a mainstay in this project, therefore our team has deliberated many times on the methods to do rapid water quality tests and how to clean the equipment that has touched the water.

The design first started off as a singular spectrometer based on the Beer-Lambert Law, where the cuvette had to be cleaned every time to ensure cross contamination was not an issue. This design includes a 3D printed sample holder with an LED to illuminate the two cuvettes, as well as a mirror to reflect the spectra onto the hole on top.

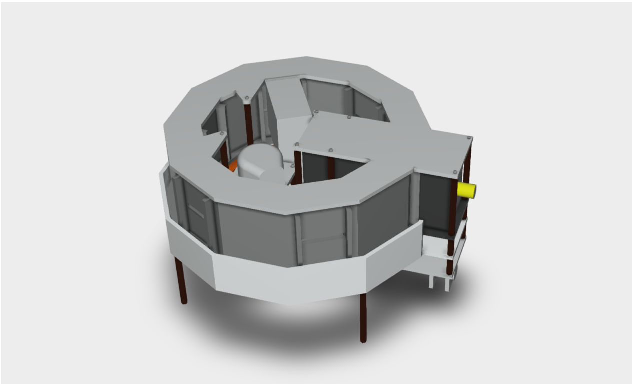
Inside the sample holder

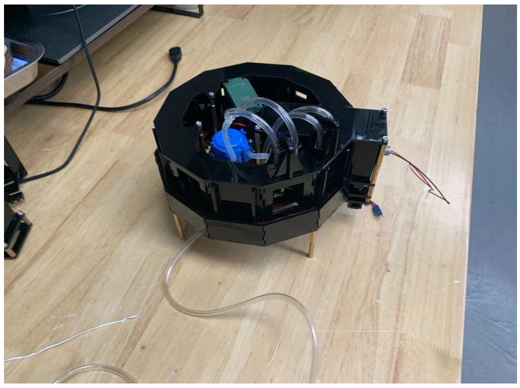
We then moved on to automatic cuvette cleaning, but that solution was too mechanically complicated and tedious, as well as concerns that this system may not clean very adequately, which led us to the revolving cuvette system.



Rough drawing of automatic cuvette cleaning

It was first designed to be linear, but after space considerations and being able to expand the system much more efficiently, we opted for a circular design at the end.



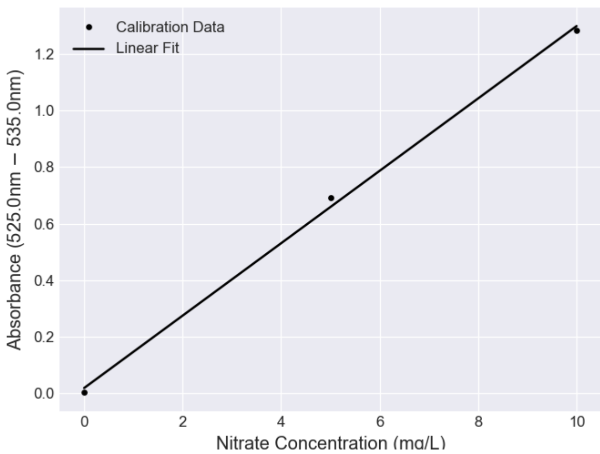


Left: 3D model of the sample holder; Right: Sample holder as it is

B. Software Design

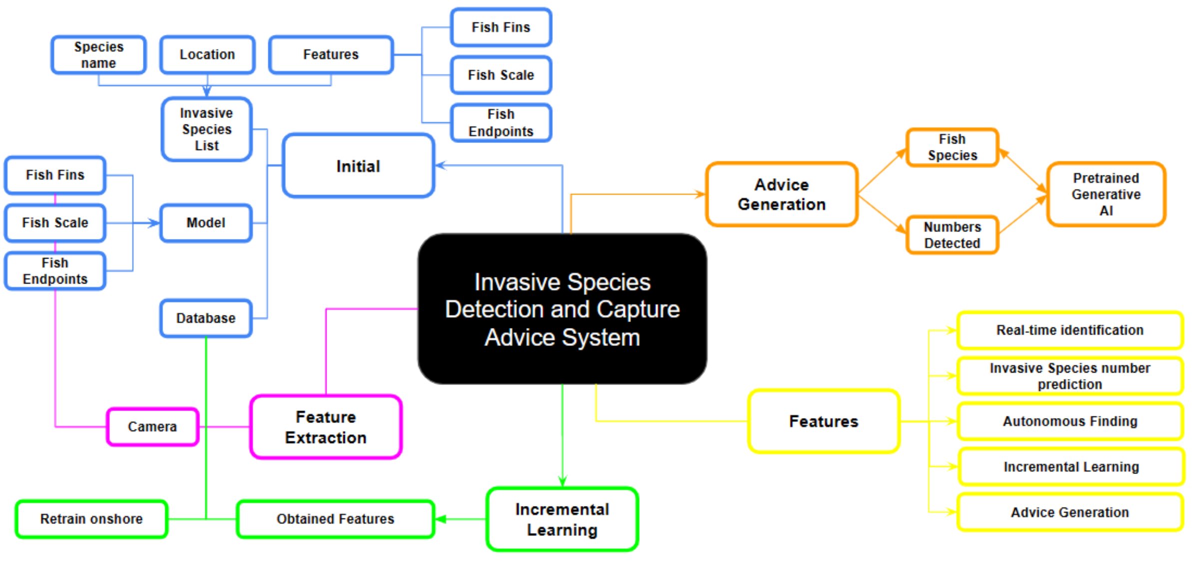
I. Nitrate Surveillance

The spectrometer calculates the concentration of nitrate in the water samples via analysing the wavelengths of the two samples given. The program will first calibrate in order to avoid any inaccuracies that may happen during analysis by using three predetermined spectra samples that are taken beforehand. Afterwards, the nitrate concentration will be steadily calculated via the Beer-Lambert Law.



Calibration graph of the software behind the spectrometer

II. Aquatic Species Monitoring



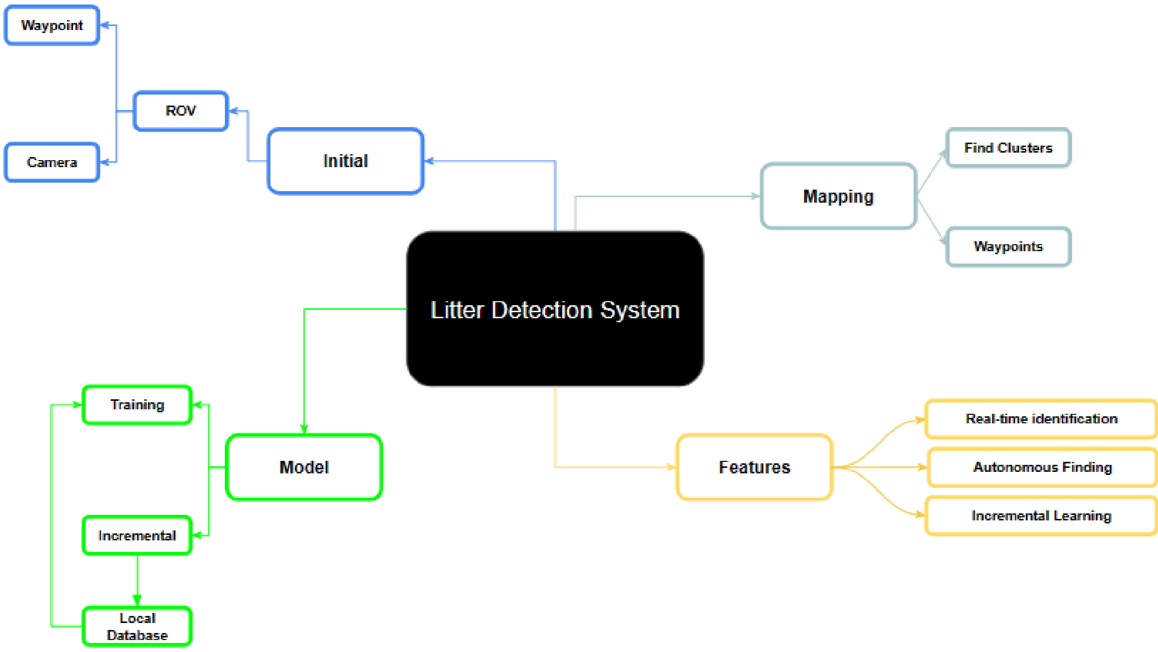
As shown in the image above, our design for the Invasive Species identification and capture advice system mainly has a few important features:

1. Real-time identification
2. Number prediction
3. Autonomous Finding
4. Incremental Learning
5. Advice Generation

With this system, the boat will be able to perform underwater identification of invasive species at different depths. After identifying the fish using its features and similarity comparison (which will be further explained in the following sector), the data will be stored in a local database for further incremental training onshore. This section is another feature of this system as it allows the robot to simultaneously operate while also improving itself. After identifying the invasive species, the robot will also be able to estimate the number of this species in the lake based on the frequency it finds the fish at, and ultimately forward this information to generative artificial intelligence to obtain advice for dealing with these invasive species.

In summary, the invasive species identification and capture advice system provides higher autonomy and less risk to ecosystems and invasive species identification.

III. Water Environment Monitoring



Our litter detection system mainly has three features:

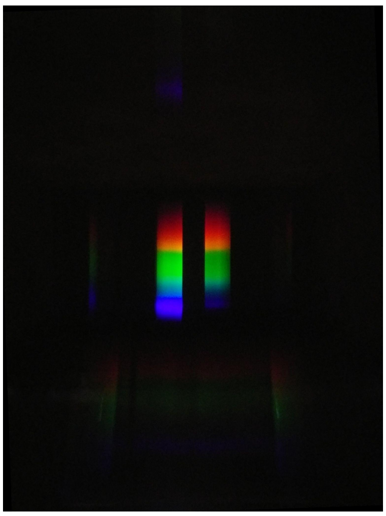
1. Real-time Identification
2. Autonomous Finding
3. Incremental Learning

With real-time identification, the boat can quickly forward the location of where litter clusters are to officials, who can then rapidly clean up the cluster before they are spread across the bed by tides or currents. Prior to this system, the main method for finding litter underwater was to use manual labour. With the implementation of our system, alongside incremental learning, our boat will be able to perform litter finding without the intervention of humans while simultaneously improving its accuracy.

Functionality and Features

I. Nitrate Surveillance

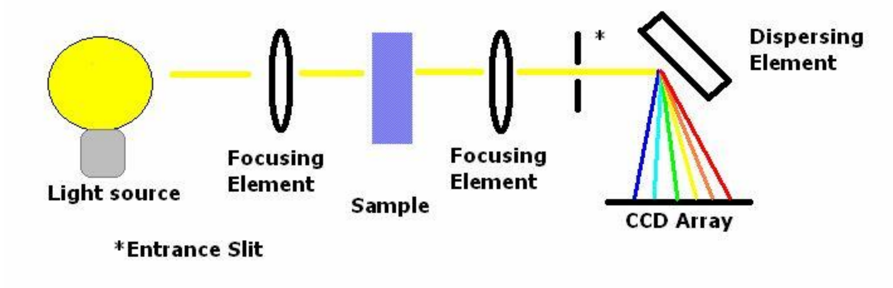
The boat detects nitrate concentration using the Beer-Lambert Law, where the light absorbed illustrates an equivalence with nitrate concentration in the water. After running calculations, the minicomputer onboard will log down the nitrate concentration in that particular place via gps positioning. As this data is collected in real time, water



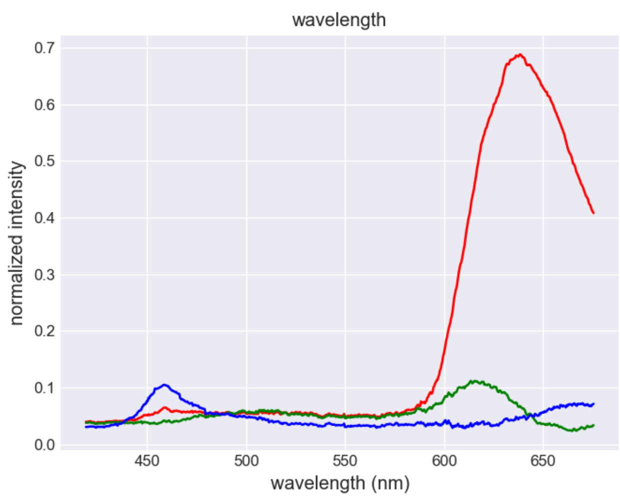
Spectra

samples do not need to be brought on shore for more thorough analysis.

Our spectrometer uses colorimetry to perform detection on nitrate. This spectrometer was built based on the Beer-Lambert law. Firstly, the water absorbs the reagent, and then the water will change its colour depending on the amount of nitrate it has in the water. Then the light inside the spectrometer will turn on, and the light will shine through a hole in the sample holder. Depending on the amount of nitrate in the sample water, some light may be absorbed by the sample. The light then goes through another slit and into a mirror, reflecting up into a hole in the spectrometer. The user can now take a photo of the spectra and directly send the image into the python code. Calibration is needed for the spectrometer to work correctly; otherwise, there is little to no preparation required for said program to function

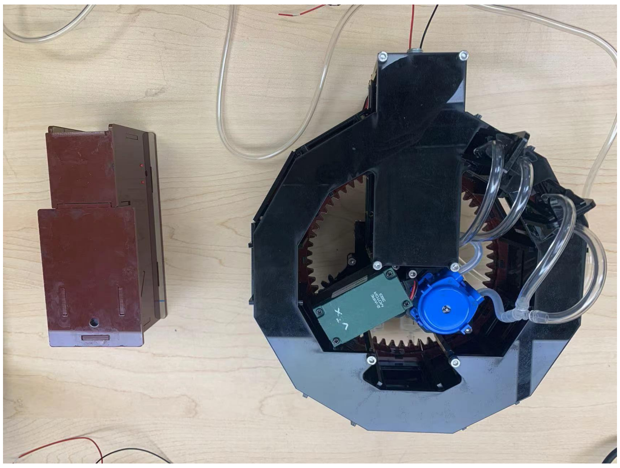


How a spectrometer works



Wavelength analysis of the spectra

Our team has designed a revolving sample machine that bestows the boat with the ability to analyse several locations at once. This works via rotating a set of cuvettes through a system. In the centre is a robotic arm that will pick up samples from the water beneath it, and put the samples into position. Then, a camera will take a photo of the spectra and upload the photo to the computer, which will then output the nitrate intensity. In the future the ability to clean them during an outing may be installed. The revolving system was made to be circular due to the limited amount of space onboard the boat, and this system allows for easy access into the chamber.

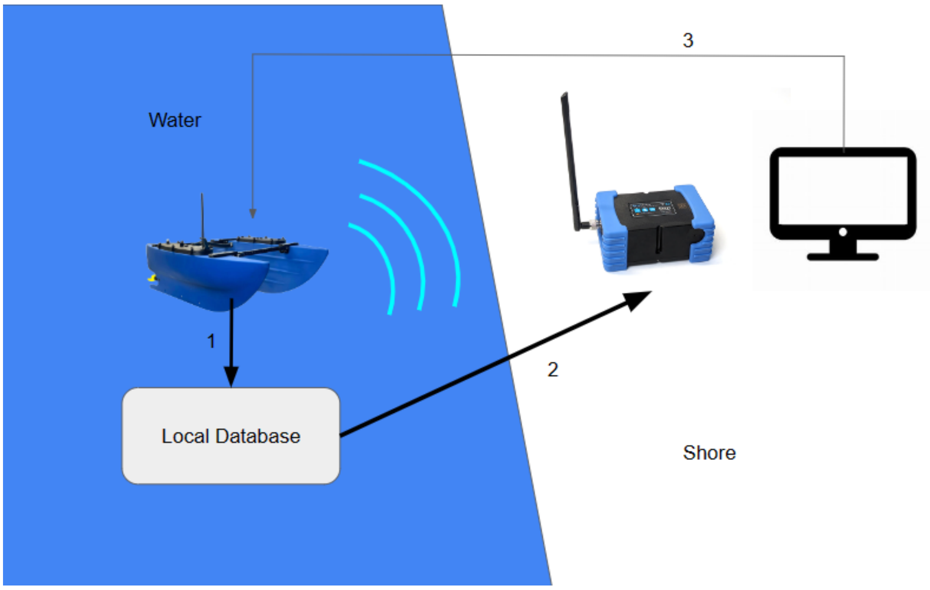


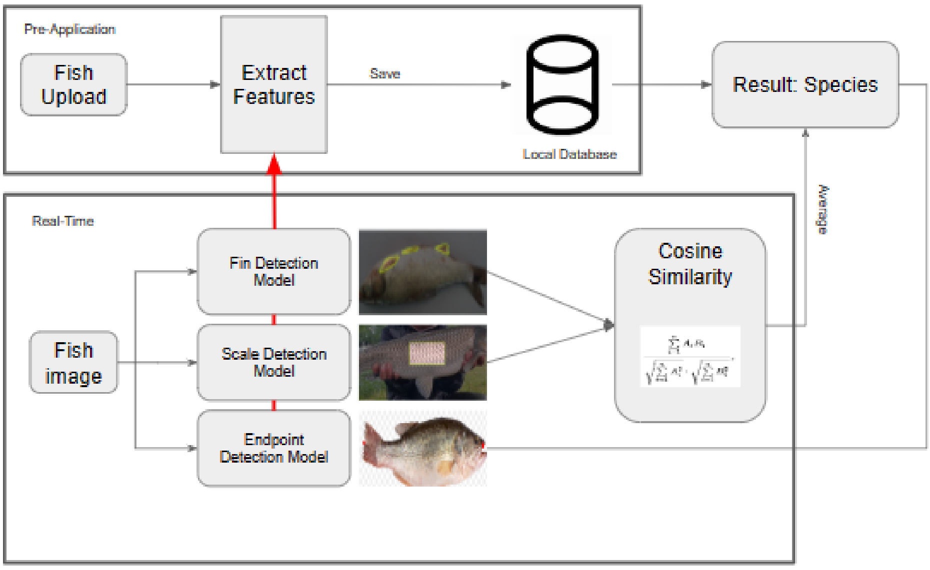
Original spectrometer (left) and the revolving system (right)

Following an extended term of data collection, it may be able to predict long-term health of a certain body of water, such as when algae blooms will happen, using long short-term memory neural networks.

II. Invasive Species Identification

The aforementioned method consists of two sections: the image segmentation phase, where the computer has to find certain characteristics of the fish, and the image comparison phase, when the computer compares the found characteristics with a given image of the fish to output the species of the fish. This process is shown in the following photo.





Method Pipeline

2.1 Fish Fin Training Model

A. Data Collection and Processing

Before the training could begin, the data for fish had to first be collected. For the purpose of identifying fish fins in an image, an initial dataset of 300 fish from different species with images of different resolutions was used.

Samples of the dataset

Amongst the initial dataset, it was found that some photos displayed cooked fishes, as shown in the following photo, which would prove to not be beneficial to the model outcome. After the removal of these images, the dataset consisted of 274 remaining images.

Sample of cooked fish

After the initial data collection, the dataset was split into 70% training, 20% validation, and 10% test sets.

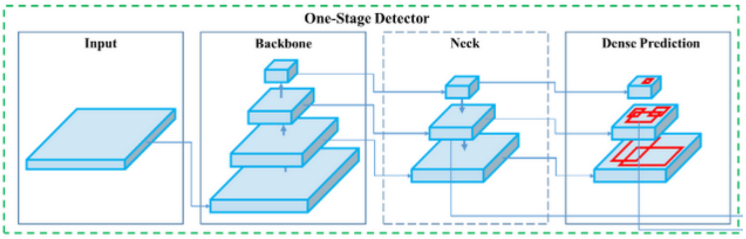
For the annotation sector, a function called *Smart polygon* from the dataset creating platform *Roboflow* was utilised to automatically find boundaries in images and mark fish fins in the image, as shown in the aforementioned photo.

B. Models

The YOLOv5 architecture is highly effective for detecting fish fins in images due to its exceptional speed and accuracy. YOLOv5 employs a single-stage object detection approach that enables it to process images in real-time. This architecture utilises a deep neural network that divides images into a grid and predicts bounding boxes and class probabilities simultaneously. For detecting fish fins, YOLOv5's ability to capture fine-grained details and small objects makes it particularly suitable. Its efficient architecture allows it to detect fish fins with remarkable precision, even in complex underwater environments or situations with multiple fish species present.

In the market today, there are mainly two types of object detection models: two-stage object detectors and single-stage object detectors, which YOLOv5 lies under. Single-stage

object detectors are composed of three components: Backbone, Neck and a Head to make predictions.

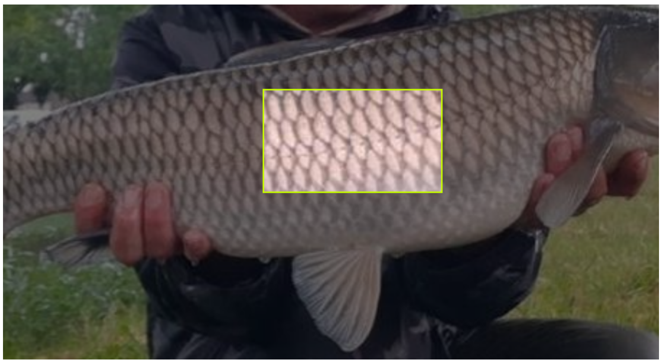


One-Stage Detector

The model backbone is mainly used to obtain important features from the given image. In the case of YOLOv5, the CSPDarknet-53 pre-trained network was used as a backbone to extract informative features (visual characteristics of an image that are relevant to identify objects) from an input image. Furthermore, PANet was used as a neck to get feature pyramids, and three 1x1 convolutional layers were used as Head to predict the locations of the bounding boxes, the scores, and the object classes.

2.2 Fish scale finding

For fish scale finding, I decided to use the same image set as the fish fin detection model. For each image, I would annotate the top left coordinates and bottom right coordinates of a box that encases a certain section of the fish's body.



Sample from the fish scale finding dataset

For this model, the YOLOv5 architecture was used again, providing higher efficiency and speed for the model's operating time.

2.3 Fish Length Calculation

The fish length calculation section is divided into two sections: *detection of the fish's endpoints and calculation*.

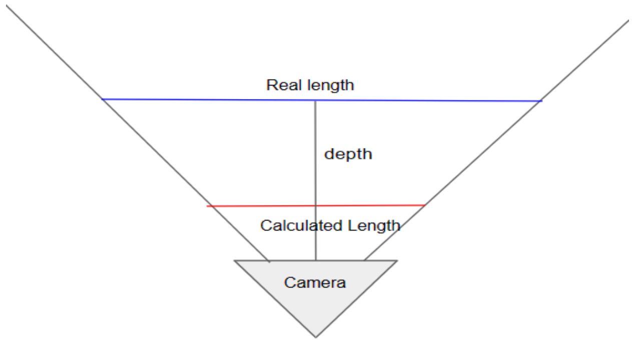
For the calculation of the fish length, the provided environment should be equipped with an RGB-D camera, which not only outputs the RGB image received, but also the depth information corresponding to each pixel in the image.

A. Fish Endpoint Detection

For the fish endpoint detection model, the same image set was used again. For the annotations of the dataset, the coordinates of the fish's head and tail was used as annotation for the image.

Sample from the fish endpoint finding dataset (Red indicating endpoints)

B. Calculation



Calculation of Fish Length (Visualised)

As shown in the image above, after visualising the camera's relationship with the length of the real fish, it can be found that the length of the fish in the image and the actual length of the fish can be calculated using the concept of similar triangles. With the help of the depth camera, the robot can calculate the ratio between the two triangles, which can then be substituted to calculate the real fish's length.

$$\mathrm{img_d} = \frac{c_{len}}{2\tan\left(\frac{FOV}{2}\right)} \qquad \mathrm{real_{len}} = \frac{c_{len} \cdot \mathrm{real_d}}{\mathrm{img_d}}$$

As shown in the images above, the depth of the fish in the image has to be calculated first. In the first equation, FOV refers to the given angle of vision for the RGB-D camera, C_Len refers to the length of the fish in the image. After obtaining the values, the real length of the fish can be calculated by using simple similar triangle concepts.

2.4 Similarity Comparison using the Cosine Similarity

After the fish features are extracted, the robot will use the cosine similarity method to find the similarity between the two images.

Cosine similarity is a metric used to measure the similarity between two vectors. In the context of image processing, it can be used to compare the feature vectors extracted from images, such as fish features in your case.

The cosine similarity between two vectors is calculated based on the cosine of the angle between them. It ranges from -1 to 1, where a value of 1 indicates that the vectors are identical, 0 indicates no similarity, and -1 indicates that the vectors are completely dissimilar.

The benefits of using cosine similarity in image comparison include:

1. Simplicity: Cosine similarity is a straightforward and easy-to-understand metric that can be implemented with relatively simple calculations.

2. Computational Efficiency: Calculating the cosine similarity between two vectors involves only basic arithmetic operations, such as dot products and vector norms. These operations can be efficiently executed, making cosine similarity a computationally efficient method for measuring similarity.

Given these advantages, the cosine similarity was decided to be used as our image comparison method.

After the species of the fish is identified, the on-boat computer can compare the species with a pre-written list of invasive species from different continents and see if it belongs to the list. This will then output if the fish detected is invasive or not.

2.5 Predicting Numbers, Providing Advice, and Mapping

After detecting an invasive species, the boat will mark the location of which it found the invasive species in. Over a course of time, the boat will have saved an average frequency of invasive species appearing at different places in a body of water in its local database. Using logistic regression, the population of this invasive species can be estimated. By forwarding the invasive species' name and population, the on-boat computer can connect to a web-based generative artificial intelligence (such as Bing) to obtain advice on how to remove these species'.

Furthermore, the average frequency at which the invasive species appears can also be used for a heatmap that shows the population density of the fish at different areas of the enclosed body of water (lakes, reservoirs, etc…). This can provide a user-friendly interface for officials to use when dealing with these invasive species.

III. Litter Detection

A. Dataset

For the dataset of the litter detection, 250 images of underwater imagery were used. In these 250 images, 40 images were marked null, which indicated that there was no litter in these images.

Sample Image marked Null

All of these 250 images were taken by Jungseok Hong, Michael Fulton, Junaed Sattar in their TrashCan 1.0 project. The images were taken by real underwater robots, meaning that the distortion and quality of the images were going to be similar to what our boat would experience. This data was then split into 70% training, 20% validation and 10% testing.

B. Training

Similar to the previous functions, YOLOv5 was also used in detecting litter. First, the images were preprocessed and shrunk into a 640 x 640 size image. Next, the images were trained for 130 epochs.

C. Mapping

After identifying trash, our robot will take note of its current location and the amount of trash detected. This will then be sent to a local database, which will use this information to output a real-time heatmap.

IV. Monitoring System with Unmanned Boat

The unmanned boat, acting as the carrier, is equipped with navigation and control systems, offers the capability of autonomously planning and navigating a pre-set route to designated waypoints, meanwhile avoiding obstacles and adapting to changing environmental conditions. This autonomous planning allows the boat to efficiently and safely navigate to its intended waypoints.

Once the unmanned boat reaches designated waypoints, it notifies the monitoring system of its arrival. So that the system can activate various operations.

Navigation and path

The two common modes:

1. Routine patrol mode: Capable of periodically monitoring at specific waypoints to ensure that the water quality remains at a stable level. Provides a systematic and proactive approach to surveillance and maintain water quality, allowing for timely interventions and the preservation of a stable and healthy aquatic environment.
2. Event-triggered monitoring: It allows for targeted data collection when specific ecological events occur, and has entered a more severe situation that requires round-the-clock real-time monitoring. Provide high-density, long-lasting sampling and analysis conducted at specific locations. This continuous monitoring aims to surveillance the situation and identify the underlying causes.

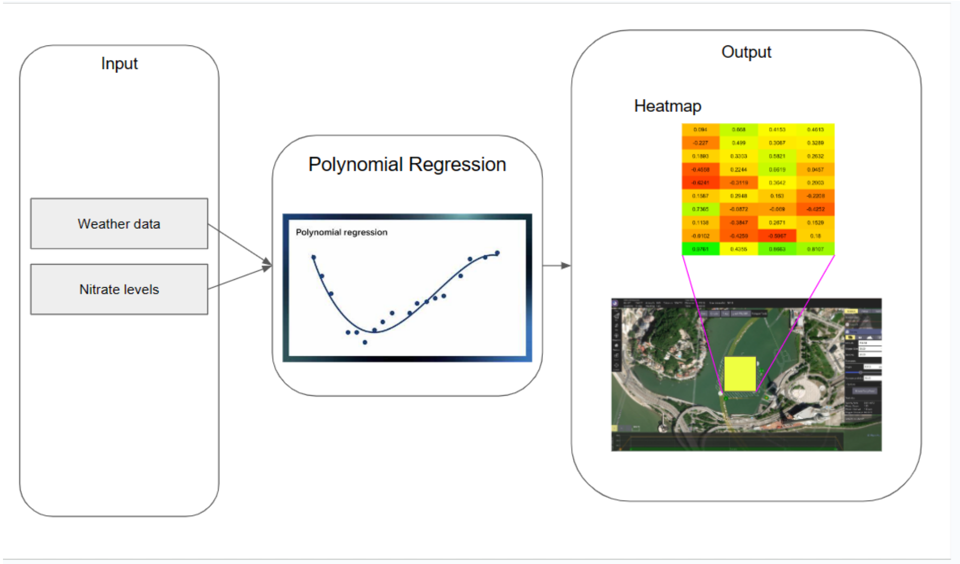
Also provide real-time data transmission, after collecting and analysing samples. The unmanned boat can transmit the data back to the monitoring system in real-time. This enables prompt analysis and decision-making based on the collected data.

One of the key features is its Environmental Possibility Prediction Based on Intelligent Analysis. By analysing previously collected dataset and its relationship with overall environmental events, we can provide opportunities and buy time for early prevention. This approach involves collecting and analysing large volumes of data from various sources, including environmental sensors and historical records.

Using advanced analytics techniques, such as machine learning and data mining, to identify patterns, correlations, and anomalies. By uncovering these insights, we can gain a better understanding of the relationship between different environmental factors and events.

IV. Mapping and Predicting the Nitrate

After being able to obtain **real-time** information on the nitrate in the water, a prediction model will have to be implemented to return predicted areas of nitrate in bodies of water.



Flowchart of the mapping system

After doing some research, we decided that the three deciding factors for the predicted location of algae would be the weather data (wind speeds, etc…), the monitored nitrate levels. Since there are more than two predictor values in this situation, polynomial regression was used to predict the location of nitrate.

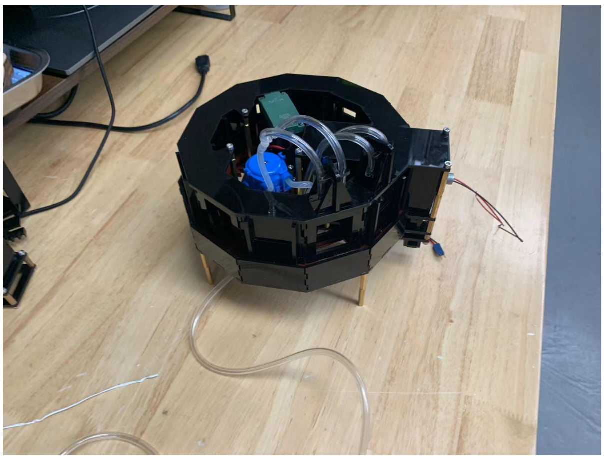
Innovation - Uniqueness

Rapid results

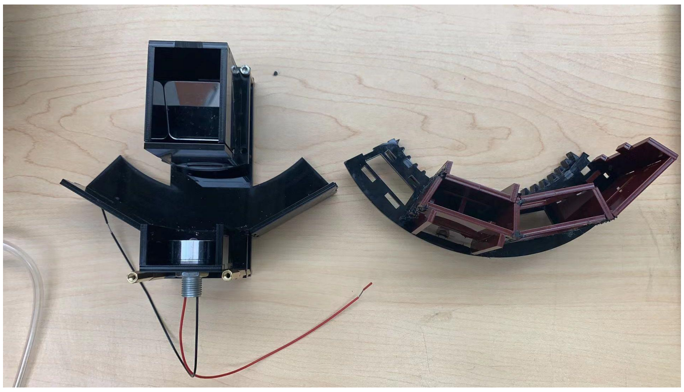
By combining accurate lightweight testing equipment and manoeuvrable autonomous boats, information regarding the health of certain bodies of water is able to be collected and analysed relatively quickly, without the need for samples to be collected onshore.

Automatic sampling system

More specifically, nitrate concentration levels are able to be calculated onboard the autonomous boat, therefore reducing the risk of contamination that comes with offloading samples onshore, as well as transporting the samples to the laboratory. The ability to analyse several areas in one outing is done via a machine that rotates with each sample, totalling six samples as a whole. This bestows the autonomous boat with the ability to sample a maximum of six bodies of water, providing that the user follows the procedure of sampling water as provided by the United States Department of Agriculture.



Revolving sample holder



Cutoff of the sample holder. The part on the right holds the water samples while the part on the left acts as the spectrometer.

High level of autonomy

In addition, risk of injury and costs can be kept down, as personnel can be kept onshore as operators of the autonomous boat, instead of in boats, which may pose some risks if planning uncarefully. Operators do not need to even be near the area of operations; instead, the boat can operate without human interference, and can sample at regular intervals.

Portability

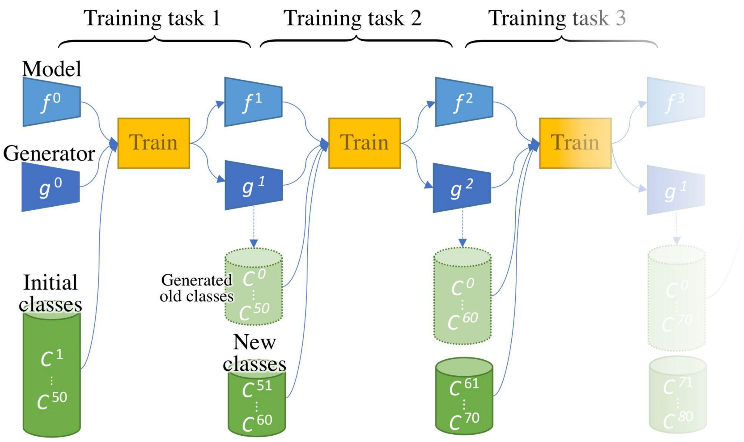
The boat is made up of two components; the sampling section and the catamaran. These two are separate, therefore ensuring the portability of the boat is high, as the catamaran part can be folded, which allows it to be transported in the back of a regular car with ease. This is in contrast with other types of boat, where the sampling section is integrated with the actual “boat” portion of the boat, which makes transportation an issue in certain cases.

Left: Boat whilst folded up;   Right: Testing boat on water

Prediction models & Incremental learning

With the deployment of our robot, which uses regression models and the monitored data to predict when there is going to be an algal bloom, companies can prepare for the algal blooms by implementing effective nutrient management practices to minimise nutrient (phosphorus, nitrogen, etc) runoff into water bodies.

Furthermore, an incremental learning system was implemented to let the robot adapt to more situations. With this feature, the robot will be able to adapt to variability in light levels, and other elements that would otherwise affect the prediction of the model.



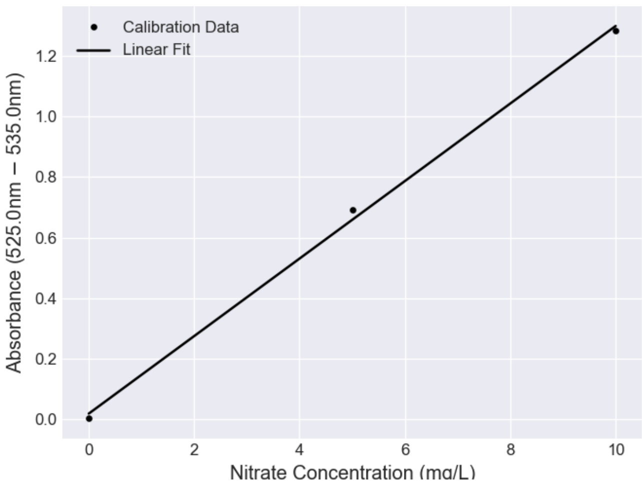
Sample Pipeline for incremental learning

Model being used for stock market predictions

Experimentation

I. Algae Detection

The results are generated by sending the spectra through python code, and it calculates the nitrate concentration in the water. It uses multiple python modules, such as os(for finding the correct file), sys(for finding the python version that the user is running), numpy(to calculate equations, such as A=elc), matplotlib(to show plots), warnings(to warn the user if the picture is landscape, and datetime(to find the current time). The spectra will have more visible colours on the right if the sample has less nitrate. In this example, the nitrate concentration is about 9.88 mg/L, or 9.89128595 ppm(parts per million), which is just below the limit set by the US Safe Drinking Water Act(10 mg/L or 10 ppm).



graph of nitrate concentration

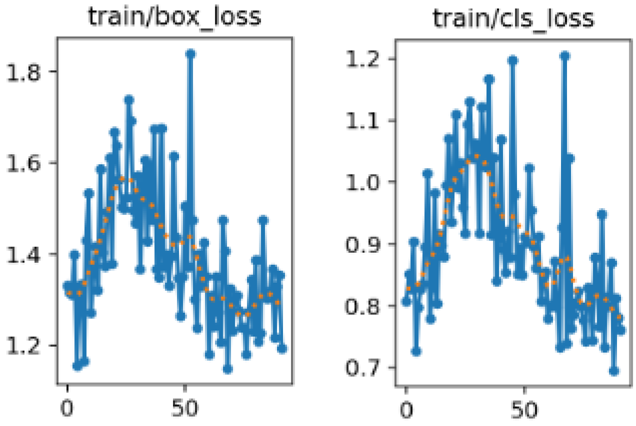
```
Nitrate Concentration: approximately 9.88 mg/L
```

output of nitrate concentration

II. Invasive Species Monitoring

A. Fish Scale detection

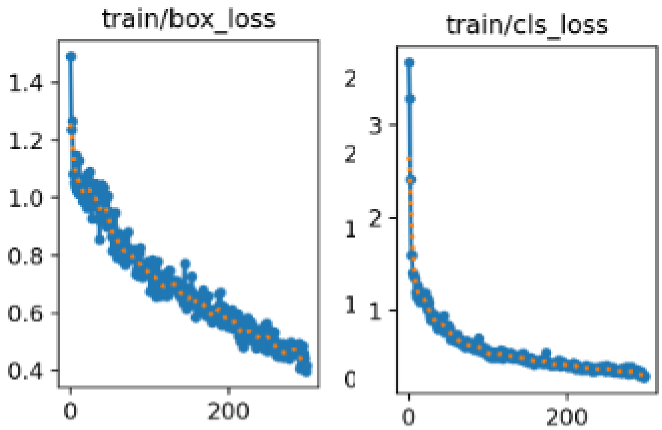
For the fish scale detection model, we trained the data with 100 epochs, and was able to get the following loss graphs:



Loss graphs for fish scale detection model

B. Fish fins detection

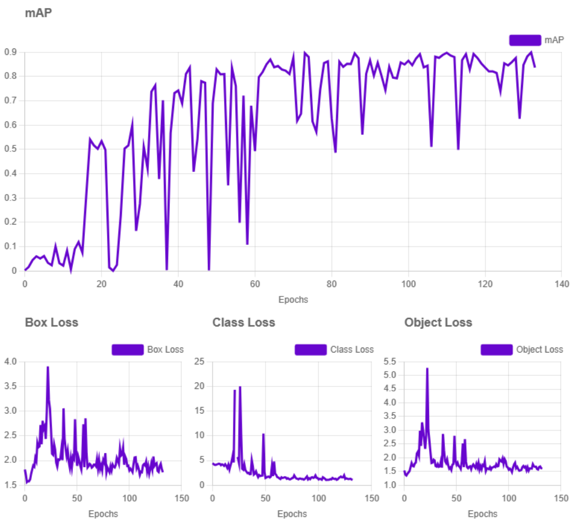
Again, after training the data for 215 epoches, we were able to obtain the following loss g raphs:

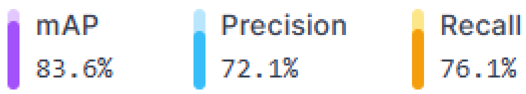


After analysing the difference between the two loss graphs, it can be said that the training for the fish scale model was less successful as compared to the fish fins detection model. This can be attributed to the difference in number of epochs and amount of images used for training. This problem can be solved with the usage of the robot as the incremental learning feature is able to mitigate the lack of data.

III. Litter Monitoring

After training the data for 130 epochs, we were able to obtain the following graphs of loss. After testing with the validation sets, we were able to get a precision of 72.1%.





Loss graphs of the model

Precision and results from validation

With the initial tests, we decided to do some further tests on the circumstances of when the model would fail. To achieve this, we decided to feed the model with images of showing the following things:

1. Clusters of trash
2. Single trash
3. Distorted
4. Undistorted

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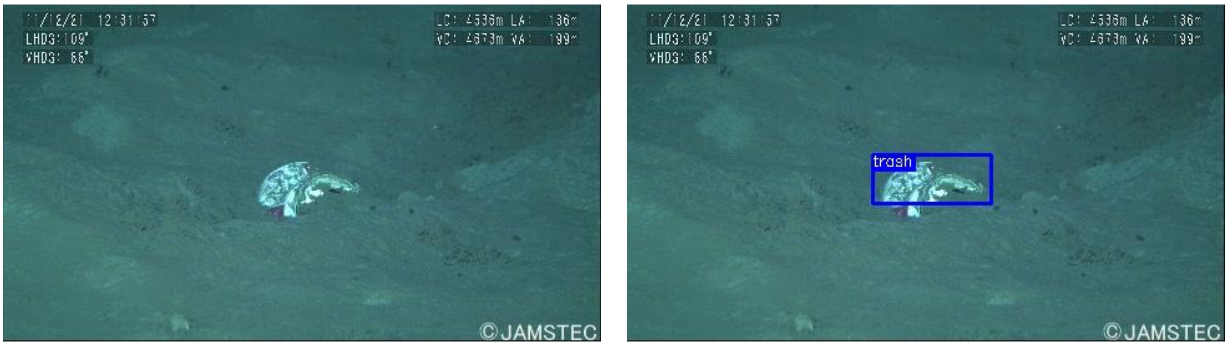
A. Clustered trash

For the clusters of trash, we used the following image (left), which contains a cluster of blue bags, and fed the image to the model. After running inference on the image, the model was able to output the following image(right). As shown, the model's capabilities lie mainly in detecting sole objects since the dataset provided showed mainly single objects on the ocean floor.

B. Single trash

Next, I tested the model for detecting single pieces of trash. For this section, we used the following image(left) to let the model run inference on. The model was able to accurately measure the pieces of litter.



Testing Images

To test if this phenomenon was not a coincidence, we decided to commit further in this aspect. To do this, we again decided to feed the model another image of a sole litter (left), and it, again, was able to detect it accurately(right). This meant that the error was due to a lack of dataset training.

Testing Images

Conclusion

Water pollution has been in the spotlight recently, with Japan's decision to release nuclear wastewater into the Pacific Ocean, leading them to receive flack from neighbouring countries. Experts have agreed that the wastewater poses little to no harm, yet water pollution still remains a serious issue. More local issues go by unnoticed by others around the world, such as harmful algae blooms like Lake Erie and Lake Taihu. Powerful, yet harmful chemicals may be used to combat these algae blooms when growth has gone out of control.

Therefore, our team has designed an Autonomous Ecosystem Surveillance Robot, or AESR for short, to inspect rivers, lakes, and other bodies of water for possible areas that are at risk of developing eutrophication and other harmful natural phenomena. This is done via a mobile nitrate spectrometer, and an AI model that scans the surroundings for potential invasive species.

In addition to water quality surveys, our boat has the ability to protect local aquatic biodiversity via the ability to detect species non-native to that area, therefore reducing the risk that native species will out-compete native species, as well as being able to resort to less harmful actions taken against these species, limiting collateral damage to native species. Coupled with the capability to map bodies of water, this provides an extremely potent tool to conserve aquatic biodiversity and ensure biosecurity.

Future Work

Our current hull has served us well, but we are planning to replace it with BlueRobotics' BlueBoat instead, as it provides more upgrades and software functions, as well as the ability to mount more weight onto the hull, due to the low thrust to weight ratio on the current hull.

Blue robotics blue boat design

We are also planning to add more water quality indicators. Even though nitrate itself does provide a good indicator of water quality, there are a plethora of other indicators that may signal other natural phenomena that would otherwise not be detected under nitrate surveillance.

Furthermore, as shown in the present experiments, the model lacks training on garbage clusters on the ocean floor. To mitigate the mistakes the robot makes during testing and application, and to also output effectively to create heatmaps, we hope to apply more initial data on clustered imagery for the litter detection model.

Lastly, we hope to implement a wireless solar charging station for the boat. Right now, the robot is only able to run for a limited amount of time before needing to recharge. With solar charging, we hope that the robot is able to calculate when its battery is going to run out and autonomously navigate to a station beside the body of water to recharge. This will lead to **higher and more effective data output** and **less human intervention**.

【評語】200016

This project aims at closing the aquatic gap in biosecurity measures by incteqrating several functions, such as water quality monitoring, aquatic species monitoring, and seabed topology surveillance is an autonomous ecosystem robot. It is also suggested that the report should follow the format including introduction, materials and methods, results and discussion, conlcusions, and reference.