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An Improved Single Short Detection method for Smart Vision-Based Water Garbage Cleaning Robot

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Abstract. These days, plastic trash is exponentially overwhelming our waterways. The catastrophe has attracted global attention at this point. As a result, protecting the environment on the water's surface has received increasing focus. Currently, manpower can be used to clean up contaminated water bodies like ponds, rivers, and oceans. Using the current cleaning approach results in low efficiency and hazard. The detection, collection, sorting, and removal of plastic trash from such water surfaces has been the subject of relatively little robotic research, despite the dire circumstances. From private sources, there are very few individual efforts to be found. In order to attain great efficiency without human assistance or operation, a fully autonomous water surface cleaning robot is proposed in this study. The robot was created to adapt to any type of water body found in the real world. An efficient object identification machine learning technique can be suggested for the creation of autonomous cleaning robots. This study improved the Single Short Detection (SSD) method to recognise objects accurately. Because of the enhanced detection techniques, the robot is able to collect trash on its own. With a mean average precision (mAP) of 94.099% and a detection speed of up to 64.67 frames per second, experimental findings show that the enhanced SSD has exceptional detection speed and accuracy.

Keywords: Plastic waste removal Robot, Object Detection, Single short detection (SSD), machine learning, accuracy, Detection speed, Mean average precision (m AP)

1 Introduction

Every year, 1.7 million people die from illnesses brought on by unclean water. Thus, 275 million individuals who consume cheap protein are affected by the marine ecosystem either directly or indirectly [1]. 3.1 billion individuals worldwide will also be unable to get 20% of their animal protein needs met. The global fisheries and tourism industries would also suffer more severe harm as a result. Especially, the plastic waste causes serious diseases. Plastic has a character of slow degradable at maximum. As a result, plastics are now ubiquitous and have negative effects on marine health, including entanglement, ingestion, protein scarcity across species, toxicity, and contamination at various trophic levels [2,3]. Eight tones or so of plastic products have accumulated inside the ocean. Like a truckload of plastic trash is being dumped into the ocean every minute, that's how it seems. Similar to this, at least 1.56 billion mask were dumped into the water in 2020 owing to the unexpected corona virus outbreak. The majority of the masks were disposable models, and in the ocean, they will take 400 to 500 years to decompose. They might spread germs and serve as a breeding place for them to grow[4]. The need to conserve water resources is so critical. The ocean's plastic dust has posed a serious threat to marine life and had long-lasting repercussions on the ecosystem as a whole. Ocean floating plastics and cleaning have received a lot of attention recently in an effort to cut pollution. The majority of plastic garbage is produced on land and travels to the ocean via interior waterways like rivers, ponds, and so on. decreasing the flow of plastic dust from freshwater rivers into the marine system is another important step. Additionally, this results in a decrease in the amount of plastic pollution in the world's oceans. In inland waters, coastal areas, and marinas, as depicted in fig 1, it is crucial to promptly pick up floating garbage [5].

Fig 1 The floating wastes in oceans, coastal area and inland waters

Traditional method of clearing that plastic garbage is mainly depends on human operations as illustrated in fig 2. Moreover, collecting plastic waste from water bodies on one shift is impossible and complicated. At the same time, the manual operation will turn into dangerous activity due to the possibilities of accidental drowning and afraid of producing polluted toxic waters [6,7]. Furthermore, the manual operation is a low-efficiency while cleaning the large area only relaying on human operations.

Fig 2 Examples of cleaning water surfaces manually

To tackle the risk of human while clearing the water surface and improve the cleaning efficiency, the autonomous cleaning robots can be replaced the traditional operation mode. Additionally, autonomous cleaning robots can access hazardous areas where humans are unable to. As a result, the cleaning robot can thoroughly clean the plastic debris. Furthermore, a high degree of automation robot can carry, contain, remove, and steer material without human intervention, greatly increasing cleaning effectiveness. It must completely cover the water surface in order to thoroughly remove plastics and other garbage from the entire waterbody [8] [9]. Therefore, creating a coverage cleaning path is crucial in order to direct the robot. The covered path planning (CPP) techniques, such as boustrophedon cellular and line-sweep-based decomposition algorithm, have been applied in the current system. The created coverage area should cover more irregular boundaries with obstacles instead of the traditional covering path planning. The motion parameters of surface cleaning robots play a significant role in setting more coverage area. The motion parameters are low turning speed and acceleration which are useful for attaining higher cleaning efficiency [10].
In this study, we develop a revolutionary autonomous water surface waste cleaning robot prototype that can clean water surfaces effectively without assistance from humans. Additionally, it can be applied to actual bodies of water, including lakes, ocean, coastal areas, and inland streams. We suggested employing a novel technique for covering path planning to increase the robot's cleaning effectiveness. The suggested CPP strategy should involve active participation in waterways with erratic boundaries and obstructions. Additionally, single shot detection (SSD) was used in the design of this work for greater accuracy.

The contribution of this paper mainly focused on the following aspects:

- We design a model of novel robot that achieves fully autonomous water surface cleaning and significantly increases cleaning efficiency.
- We propose a novel CPP method for water surface cleaning using SSD object detection deep learning method.
-

The detailed composition of this paper is listed as follows: the section 2 discusses the related work about the plastic waste removal robot in water bodies and coverage path planning. Section 3 explains the proposed prototype of robot and coverage area algorithm. The investigational findings and confabulations are offered in section 4, and the study is wrapped up in section 5.

2 Related Work

The water garbage waste collecting robots are generally termed as an unmanned surface vehicle (USV). The unmanned surface vehicles can be used for various applications such as for transportation, surveillance and research. The researcher in [11] was designed robot boat aiming at autonomous transportation using multiple urban waterways robot boat. The size and shape of the robot boat has been modified for easiest way for the autonomous transportation. Peng et al [12] creates a USV for doing hydrographic survey in the waterbodies. The invention is mainly for develop a chart at nearshore shallow waters. Similarly, Maawali et al [13] develops an unmanned surface vehicle for managing the oil spill among any waterbodies. Likewise, Shojaei et al [14] initiates a methodology for using a small USV for building management such as structural health monitoring.

In literature many water surface robots have been developed and studied. However, in that mainly water surface cleaning robots gained attraction among researchers and people. The articles [15] showed some of the water surface cleaning robots have been illustrated. And in that some of the water waste collecting robots requires manual operations such as remote control [16], also these types of robots couldn't collect the garbage effectively. In that time, Hasany et al [17] proposed autonomous water surface cleaning robot with navigation for small water bodies. However, the water surface cleaning robot's operating time is relatively limited and it only has a little garbage can. Additionally, it has only been evaluated for small water bodies, such as swimming pools, making it difficult for daily use. The water surface cleaning robot in [18] has been designed without any mechanical design. This robot can be used for checking water quality also. In conclusion, there are still two issues with the water surface cleaning robots that are currently available. One is that the robots have a relatively modest level of automation. For a thorough cleanup of the water area, the path planning is not mentioned. The other is that while the water bodies used for testing are straightforward, the robots have a difficult time adapting to complex real-world environments.

In [19], the researcherChen, J et al. designed a mechanical semi-automatic drainage water cleaner for cleaning drainage pipes. The drainage pipes are very dirty and sometimes filled with poisonous gas. Hence, it is harmful for human life while cleaning the drainage system. The mechanical portion in the suggested cleaner is for replacing the manual work required for drainage cleaning system. The drainage cleaning vehicle can be designed for reducing the manual efforts as it is very danger for toxic and in toxic gas wastes thrown into the drainage [20]. The automated system was designed effectively for disposing drainage waste. To achieve automatic control of sewage waste water treatment, a Siemens PLC controller was utilised in the drainage wastewater treatment system to regulate the stepper motor, compressor, gas exhauster, pressure valve, liquid level, flow, and other analogue variables.

Jeon, C.Wet al., [21] explains in depth the process for transitioning manual work to an automated system. With the resources at hand, the suggested design is very inexpensive and effective. This technique is especially intended to lessen the possibility of human loss while cleaning the drainage line. The researcher created a drainage cleaning machine to overcome the limitation. A similar electronic bucket, or "e-bucket," was created by the researcher in [22] for a drainage cleaning system. Because the e-bucket can raise sewage, it can be utilised to treat this waste with evaporation. With the use of an ARM board, wet waste in this system was transformed into dry waste. After taking the sewage waste from drainage, given to the government bank without any bacterial affection. Rahul et al [23] aims to mitigate the global warming effects and wants to save power for treating waste water management. Thus, he proposed automatic cleaning of waste water. Nitin sall et al [24] suggested a waste water technology not for removing a pollutant particle but destroy the pollutant from a drainage system. The waste water is from homes, business industries, commercial activities is called waste water. The primary goal of the investigation would be to determine whether the chain can sustain the safe load suggested by Nikhil et al. [25] and the use of finite element modelling. To determine the impact of loads (tension) on the link, F.E Analysis would be applied to the chain's design. For the purpose of benchmarking the research, an existent chain link was utilised. Similarly, Daniel et al [26], illustrates a drainage cleaning system that are used to remove garbage and cleaning the drainage pipe. And the proposed system consists of three parts such as propeller, the cleaner and the pan. All the components have been combined and form a drainage cleaning machine for its effective operation.

For instance, Li et al. [27] developed a water colour isolated perception-oriented USV (WC-USV) that is capable of self-governing wayfinding, hindrance evasion, water model assortment, water quality dimension, weather data quantity, and remote-control operations. It consists of an autonomous surface vehicle platform with data collection and gearbox modules, a ground control station, and a gearbox module. Ferri et al [28] developed a small size Autonomous surface vehicle (ASV) for measuring hydrocarbon and heavy metal concentration. And the design consists of miniaturized sensors for collecting water samples. Moreover, here VFH+ machine learning algorithm have been installed for avoiding the possible collisions. The collision is mainly because of laser scanner, sonar and so on. then the researcher Madeo et al [29] proposed an Unmanned surface vehicle named as a water environmental mobile observer. The engineered vehicle may track the sensors' salinity, dissolved oxygen, pH value, and oxidation-reduction parameter. An autonomous, intelligent USV that can cruise and monitor water quality was proposed by Cao et al [30]. The suggested intelligent USV is capable of analysing turbidity, total dissolved solids, and pH values. In order to gather high-resolution measurements in shallow coastal habitats, Cryer et al. [31] developed an autonomous surface vehicle that can monitor and analyse conductivity, temperature, depth, oxygen dissolved, nitrate, colour dissolved organic matter, and turbidity. In this way, the autonomous cars increase the scope of their time- and space-based surveillance. The extension of proximity can increase the usage of ASV in ongoing weather monitoring and real-time marine applications. They have well-matched computing systems for intelligent sampling, including reconciling sampling [32] and ideal specimen [33], albeit not all modern vessels are equipped with these. Coordination between autonomous vehicles with various attributes for various uses can also improve the effectiveness of the monitoring [34]. These benefits account for the widespread use of autonomous vehicles in complicated, distributed, and autonomous water quality monitoring systems. ASVs, in particular, can be seen of as inexpensive properties for water surveil carried out utilising moveable testing techniques because they are capable of remote tasks and safe navigation. In comparison to AUVs, Cao, H et al are also less complex and more affordable monitoring tools [35].

With the recent advancement of robots today, many researchers were tried to develop robots for cleaning purpose [36]. Even though many robots were coming into market, there is still need further development [37]. Even, semimanual garbage cleaning robot were in practice for collecting plastic waste from waterbodies. But the semimanual garbage collecting machine has very large in size and so that it may be constrained to use in bigger areas. Therefore, it is impractical to extract small-density waste from small waterbodies using garbage cleaning vessels. Such vessels are also hindered by their incapacity to recognise which object has to be removed and by the possibility that their exhaust emitted may result in secondary pollution. For the purpose of removing floating trash from water surfaces, some intelligent cleaning robots have been created. Kong et al. [38] created a smart water waste scrubbing robot system with an image module, a motion control module, and an acquisitive segment using the YOLOv3 for trash exposure, the sliding mode controller for image-based trailing and navigation, and the practicable acquisitive approach for moving garbage acquisitive and assemblage.

Wang et al.'s [39] proposal for an autonomous robot to remove trash from a lake's surface made use of the Manoeuvring Model Group (MMG) model technique to simulate the robot's hydrodynamics. For the purpose of collecting floating plastic bottles, Ruangpayoongsak et al. [40] created a floating garbage scooper robot. The YOLOv3 algorithm was updated by Li et al. [41] to create a vision-based water surface garbage capture robot for real-time rubbish detection in dynamic aquatic situations. Some of the review is discussed in Table 1. From the review, we can conclude that there is some lacking of work in the automatic detection and cleaning. So this paper going to concentrate on these both areas.

Table 1. Review paper discussion

Ref	Function	Sensor	Algorithm
[27]	Hindrance evasion	LiDAR	LOS-based GNC Algorithm
[28]	Hindrance avoidance	Navigation radar	IACO Algorithm
[29]	Hindrance detection	Vision Sensors	Skip-ENet Algorithm
[30]	Watermark and hindrance recognition	Camera	U-net CNN Algorithm
[31]	Hindrance evasion	LiDAR	ATESOA algorithm
[32]	Hindrance evasion	Microwave radar, 4G camera	-
[32]	Water quality monitoring	Chl-aturbidity, water dissolved oxygen, water conductivity, oxidation-reduction potential, water temperature, salinity, Ph sensors	-
[33]	Hindrance avoidance	Laser scanner. Sonar, Alimeter	VFH+algorithm
[33]	Water eminence Observation	Chemical sensors (Hg, Cr, Cd and dispersed oil)	-
[34]	Water eminence Observation	Ph sensors, ORP sensor, salinity sensor, dissolved oxygen prob	-
[35]	Water eminence Observation	Ph sensor, TDS sensor, turbidity sensor	Ensemble learning algorithm
[36]	Water eminence Observation	CTD, DO, Ph, Pco2, nitrate, chlorophyll fluorance, CDOM, turbidity, DOC sensors	-
[37]	Water surface cleaning	Vision module, Grasper	YOLOv3 algorithm
[38]	Water surface cleaning	Conveyor belt	-
[39]	Water surface cleaning	Camera, waste scooper	-
[40]	Water surface cleaning	Camera, collection box	YOLO v3 algorithm
[41]	Hindrance avoidance	Ultrasonic sensors	Threshold-based obstacle avoidance algorithm
[41]	Water quality monitoring	Ph sensor	-
[41]	Water surface cleaning	Vision sensor, salvage net	Hue-based colour filtering algorithm

3. Proposed works

The proposed system architecture displayed in Fig 3. The proposed model includes the following sections such as power module, communication module, position module, waste detection, remote human-machine interface. A high-resolution vision sensor and a water surface cleaning equipment make up the water waste cleaning machine. Pixy CMU cam5 vision sensor was employed in this case. The sensor is made up of a twin core NXP LPC4330 processor that can run at a frequency of 204MHz. Additionally, the sensor has an Omni vision image sensor, 264k RAM, 1M Flash, and communication interfaces for UART, SPI, I2C, and USB.

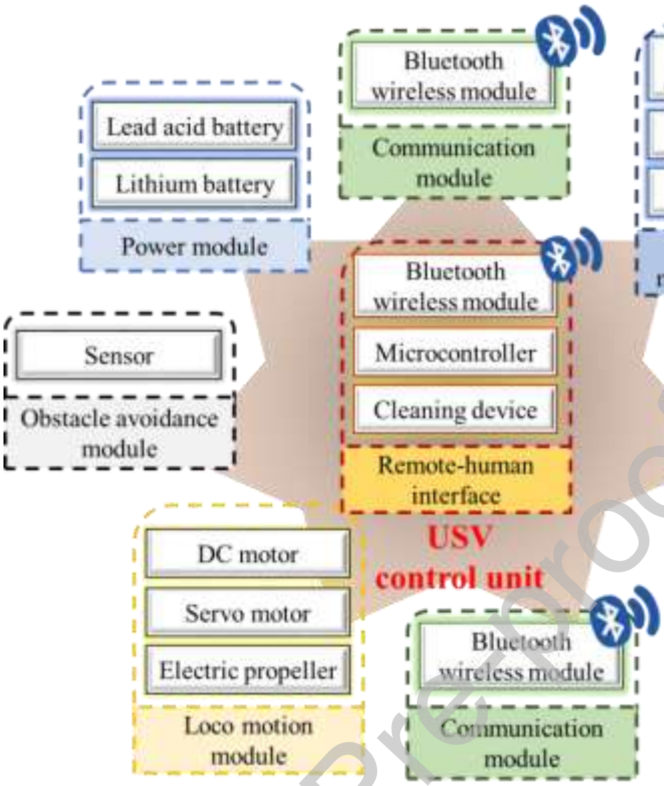

Fig 3 System architecture of the proposed USV

The vision sensor follows hue-based colour filtering algorithm for detecting the objects. The hue-based colour filtering method is termed as a colour connected components algorithm. And the hue-based colour filtering has been code on the processor NXP LPC4330 by using C++. The hue based colouring algorithm operates with high-speed, efficient, reliable. The word ‘hue’ means colour. The hue-based colour filtering algorithm calculates colour (hue) and saturation level of red, green and blue pixel [42]. The colour pixels are driven from the image sensor and these are the primary colour filter parameters. Generally, the colour of an object won’t change unless or until the strong exposure of the light. Due of its distinctive hue, which makes it easy to discern from its surroundings, a red object is used in this paper to symbolise the floating trash when cleaning the water's surface [43]. The suggested water surface cleaning robot can therefore detect floating trash accurately when the hue-based colour filtering algorithm is used.

The two DC gear motors and salvage net that make up the water surface cleaning system are used to clean and gather floating trash. The salvage net is used to raise and lower using bobbins to capture floating trash. The DC gear motors are powered by a motor driving module through the Arduino microcontroller. The vision sensor of the water waste scrubbing device is the responsible for noticing the floating garbage. Here, red colour objects are considered as floating garbage. The vision camera can be mounted on the front of water surface cleaning device. Then, the cleaning machine automatically track and collects the waste out of the water bodies by using effective water surface cleaning algorithm. The images are captured by series of array ranges X and Y. The range of X and Y coordination will be from 0 to 319 and from 0 to 199. At first, the garbage images were captured by the vision sensor that fitted on the water surface cleaning device. And the direction of the device can be changed by the X coordinates.

The water waste scrubbing environment should face five situations as follows. the water waste collecting device should turn all directions with degree of freedom. For that the device depends on the x and y coordinates. Suppose, the robot wants to turn left direction about 30°, the x coordinate has to locate between 0 and 63 degrees. If so, the water garbage collecting device knows there is a waste in the left side. Then, the device drives the servo motor to control the rudder to turn left about 30°. Suppose, the robot wants to turn left direction about 15°, the x coordinate has to locate between 64 and 127 degrees. If so, the water garbage collecting device knows there is a waste in the left side. Then, the device drives the servo motor to control the rudder to turn left about 15°. Similarly, if the device requires to go on straight direction, the algorithm has to set the x coordinates between 128 to 190. Then, the device will understand, it has to collect the garbage in front of them. Suppose, the robot wants to turn right direction about 15°, the x coordinate has to locate between 191 and 253 degrees. If so, the water garbage collecting device knows there is a waste in the right side. Then, the device drives the servo motor to control the rudder to turn right about 15°. Suppose, the robot wants to turn right direction about 30°, the x coordinate has to locate between 254 and 319 degrees. If so, the water garbage collecting device knows there is a waste in the right side. Then, the device drives the servo motor to control the rudder to turn right about 30°.

Two Arduino microcontrollers with a 16 MHZ operating frequency make up the projected USV's primary control system. One of the microcontrollers in charge of steering, avoiding obstacles, and cleaning the water's surface. Additionally, another microcontroller is in charge of navigation. The motion segment, aligning segment, hindrance evading module, water waste scrubbing module, message module, and power module are all directly connected to the control unit of the proposed USV. Additionally, in order to confirm the USV's movement trajectory, the multi-sensed data will be transmitted to a human via a human-machine interface module. The projected USV's suggested locomotion module includes an electric propeller. Direct current motors can control electric propellers, and servo metres can control rudders. With the aid of the motor drive module and Arduino microcontroller, the direct current motor and servo metre can be controlled. Through connection, the DC motor is connected to the electric propeller to control propulsion speed. The servo metre is in charge of regulating the rudder's steering blade's thrust direction. The projected USV has a GPS module affixed to it for navigational purposes. The USV's movement trajectory during travel can be generated using the positioning module. After then, the data for the location coordinates as water sampling points will be kept. The GPS module uses a GPS receiver that offers less than a second for time-to-first-fix acquisition. The GPS receiver consists of an antenna, a radio frequency (RF) satellite signal receiver, and an interface device with a CPU and a base band processor for processing GPS signals. The suggested USV's GPS coordinates can be transferred in real time from the Arduino microcontroller to the distant human-machine interface using a connecting module.

The obstacle avoidance module incorporates a pair of ultrasonic sensors positioned on the front left and right sides of the intended Unmanned Surface Vehicle (USV). These sensors have a detection range of 15 degrees ahead of the USV. Real-time distance calculations between the vehicle and obstacles are performed by an Arduino microcontroller. The ultrasonic sensors are responsible for detecting the presence of obstacles. When the calculated distance exceeds or falls below predetermined threshold values, the USV employs a threshold-based obstacle prevention algorithm to evade potential collisions. The specific threshold-based algorithm proposed for collision avoidance is visually depicted in Figure 7. Initially, the algorithm computes the distance between the vehicle and the obstacles and also the direction of the garbage left L or right R by the ultrasonic sensor implemented on front of USV. Then there may be four situations for the possibility of collision avoidance: The USV has to go straight when L is greater than 65 cm or L is less than 10 cm and R is greater than 65 cm or R is less than 10 cm. by following the above condition, the vehicle can understand there is no obstacle to avoid, so the vehicle can go front side. Suppose, if there is an obstacle at left side, the vehicle should go right direction. For that the vehicle should fall as L is located between 10 and 65 cm and R is located greater than 65 cm and less than 10 cm. The servo motor then moves the rudder in a direction to the right once the algorithm concludes there is an obstacle in the vehicle's left front side. The control changes into L are bigger than 65 cm, L is less than 10 cm, and the control R is located between 10 and 65 cm if the USV wishes to turn to the right. The servo motor moves the rudder to the left when the algorithm detects that there is an obstruction in the right front side of the vehicle. In the event that the obstruction is in front of the USV, the vehicle should reverse course. L should be positioned between 10 and 65 cm, and R should be positioned between 10 and 65 cm, as the control. When the algorithm detects an obstruction in front of the USV, the rudder is changed by the servo metre to turn 180 degrees.

The intended USV operates on a 6V lead-acid battery, offering a moderate capacity of 2.3 Ampere-hours. For the message module, two Bluetooth wireless modules are utilized. Bluetooth technology is widely recognized for its efficient low-power data transmission capabilities. In the proposed USV, the Arduino microcontroller facilitates the transmission of GPS coordinates to a remote human-machine interface through the Bluetooth wireless module. The Arduino microcontroller, integrated into the USV, transmits the GPS coordinates to the remote human-machine interface via the Bluetooth wireless module. To ensure smooth communication, the Bluetooth module establishes a connection between the USV and the remote interface, enabling the seamless transmission of GPS coordinates. The remote human-machine interface encompasses various operational interfaces, including the system operating interface, manual control interface, movement trajectory interface, and water garbage monitoring interface. These interfaces are designed to facilitate remote monitoring and control of the USV's functionalities. The signals are measured and stored at a storage path via the system operational interface. Additionally, this interface displays the trip time. The proposed USV turning directions of go forward, turn left, turn right, and turn around are manually controlled via the manual control interface. Additionally, the user has the option to halt the vehicle by pressing the stop button in order to stop it from sailing the USV. The movement trajectory interface will show the trajectory's movement in real-time when the USV is sailing. Based on the GPS coordinates provided by the positioning module, the direction will be updated. The USV's location will be updated by the water garbage monitoring interface using GPS and an obstacle detection algorithm. The prototype model is displayed in Fig 4.

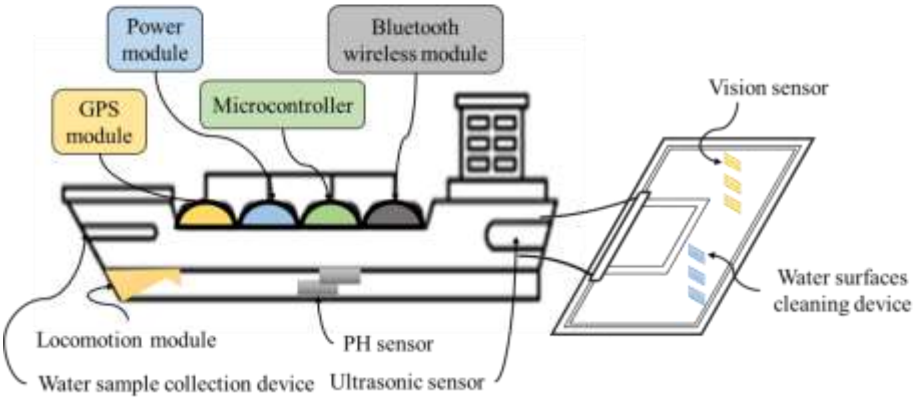

Fig 4 Prototype structure

3.1 Autonomous USV based on Single Shot Detector (SSD)

In this section the waste is detected with the help of deep learning model, which is the main model in the proposed work. The conventional SSD network is consisting of a base network and an object detection network as shown in fig 5. The traditional model behaves more accurate because of feature mapping of different layers in an image. However, degradation is a serious issue over the traditional algorithm. ResNet works well because of its structural residual block, which can be reduces the effects of degradation. Hence, in this work integrate ResNet framework with SSD detection algorithm for the effective recognising of the waste from the water. Here we are adding layers after the conv5 block, and predicting scores and box offsets from conv3, conv5, and the additional layers. ResNet -50 is a one of the main CNN architectures with 50 deep layers. Usually, if the layer increase, the quantity of parameters increases respectively. Since, this increases the complexity of the model, the learning process needs high computational power and memory. Also, one of another issue is vanishing gradient problem. These issues are solved by the ResNet model with the skip connection. Joining the real input to the output of the convolution block is mentioned as skip connection. The skip connection is mentioned in Fig 6.

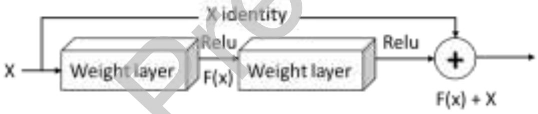

Fig 5 Skip connection

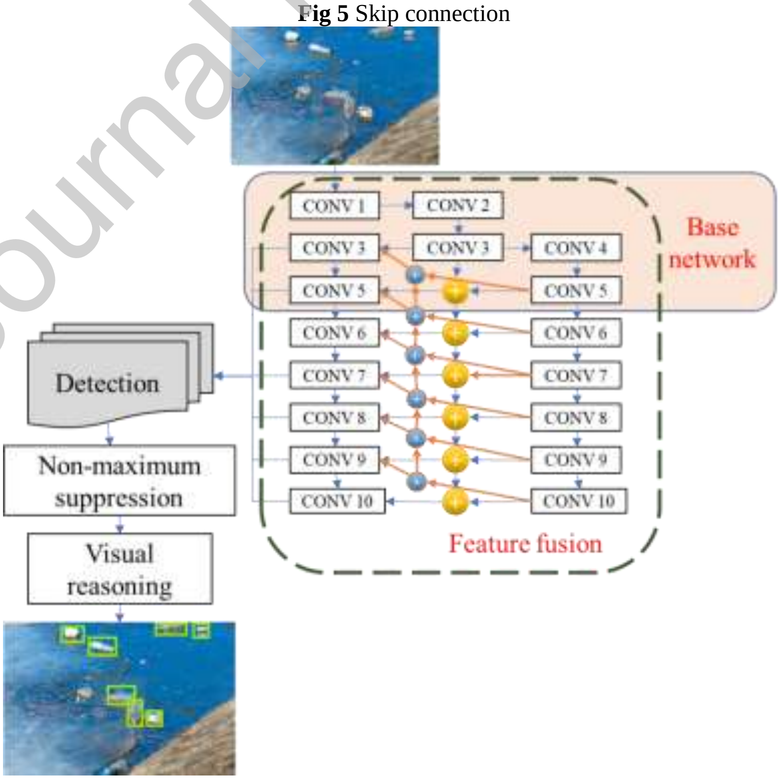

Fig 6 The Modified SSD algorithm

4. Experiment Results and Discussion

The experiment, which was carried out using Python 3.7, was implemented using the free and open-source SSD Resnet framework. The parameters are listed in table 2 for the pre-training ImageNet data set used in this study.

Table 2. The parameters of pre-training

Parameters	Batch size	Image size	Epoch	Momentum	Learning rate
Value	8	512	205	10.2	0.002

According to the testing findings, a customised SSD can give the robot precise and real-time object detection. In response to the dynamic and complicated environment, high-speed detection can process the image in real time and give the robot the object position information in real time. Even while several CNN algorithms have significantly improved accuracy, the two-stage network's computational load prevents real-time detection from being possible. In a nutshell, customised SSD performs better than the competition in terms of speed and accuracy and can significantly increase the capacity of autonomous cleaning robots. The suggested algorithm performs better than those in prior studies and is appropriate for autonomous cleaning robots based on the aforementioned results. A better dataset, however, is necessary for greater robustness in complicated aquatic ecosystems. Additionally, the pruning method, which is useful in datasets with a limited number of classes, is the main contribution of this work. However, because the pruning procedure shrinks the network's size, this technique performs somewhat worse when tested on datasets with more classes, like COCO. The trimmed network will not be enough if the dataset contains additional categories of items. Therefore, additional study is required to enhance the performance. The Acquafresh dataset samples are displayed in Fig7.

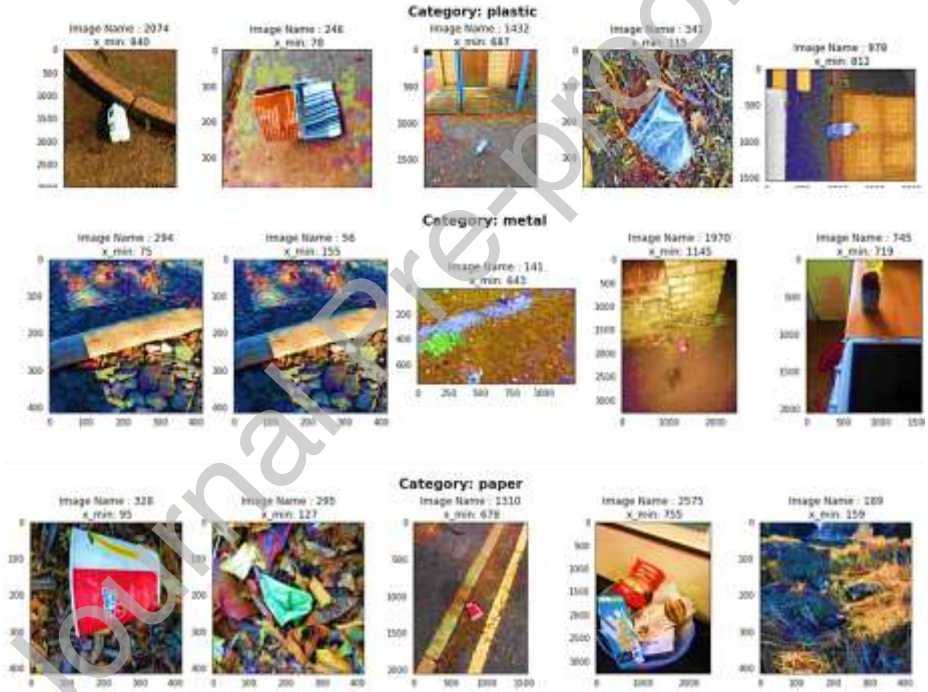

Fig 7. Database sample

Table 3. The success rate of garbage detection by the vision sensor and modified SSD algorithm

Distance/Angle	-30°	−15°	0°	15°	30°
40cm	100%	100%	100%	100%	100%
70 cm	100%	100%	100%	100%	100%
100 cm	93%	98%	99%	99%	94%
130 cm	85%	95%	97%	98%	92%

The test was run to see if the planned USV could simultaneously avoid obstacles and clean the water's surface. The suggested USV initially cruised the lake autonomously and completed the hurdle avoidance challenge using the threshold-based obstacle avoidance algorithm. After being aware of the floating trash, the proposed USV might apply the water surface cleaning algorithm to gather and clean it. Finally, the proposed USV may perform the tasks of water quality assessment and water surface cleaning, followed by the obstacle avoidance task and an automatic return to the starting location. The trash floated on the water is detected is shown in Fig 8. The Table 4. Presents the comparison between some classic algorithm for garbage detection in water.

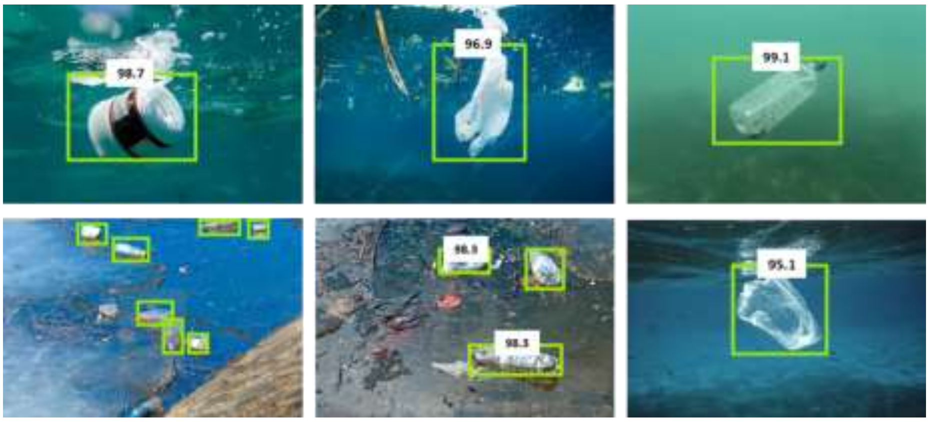

Fig 8. Floating Garbage

Table 4. The comparison between classic algorithm and modified SSD algorithm

S.No	Algorithm	Accuracy
1	CNN	69%
2	VGG-16	72%
3	Inception-v3	87%
4	Proposed	94%

5. Conclusion

This study aimed to develop an unmanned surface vehicle (USV) capable of navigating obstacles and collecting floating debris. The proposed USV architecture consists of several key components, including the primary control unit, motion module, location module, hindrance evasion module, power module, water waste scrubbing system, message module, and human-machine interface. Through extensive testing, we have successfully demonstrated the USV's effectiveness in tasks such as water surface cleaning and obstacle avoidance. Once a polluted water area is identified, the USV can accurately collect GPS coordinates of the water sampling location and transmit them to a remote human-machine interface for recording and display purposes. Simultaneously, the USV employs a customized Single Shot MultiBox Detector (SSD) algorithm for autonomous tracking and collection of floating debris on the water's surface. Remarkably, when the floating garbage falls within the visual range of -30° to 30° in front of the USV and is positioned between 45 and 75 cm from the USV, the success rate of debris identification reaches 100%. To further enhance the USV's capabilities, future efforts will involve testing the system in more challenging field scenarios to ensure reliability and stability in water surface cleaning. Additional sensors and algorithms will be incorporated into the USV to bolster its obstacle avoidance abilities, enable water quality assessment, and improve the efficiency of surface cleaning processes.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Ethics Approval and Consent to Participate

Not applicable.

Competing Interests

There are no competing interests.

References

1. M. -D. Li, X. -C. Cui and S. -W. Chen, "Adaptive Superpixel-Level CFAR Detector for SAR Inshore Dense Ship Detection," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4010405, doi: 10.1109/LGRS.2021.3059253.

2. J. Zhang, M. Xing, G. -C. Sun and N. Li, "Oriented Gaussian Function-Based Box Boundary-Aware Vectors for Oriented Ship Detection in Multiresolution SAR Imagery," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5211015, doi: 10.1109/TGRS.2021.3095386.
3. C. Qin, X. Wang, G. Li and Y. He, "An Improved Attention-Guided Network for Arbitrary-Oriented Ship Detection in Optical Remote Sensing Images," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 6514805, doi: 10.1109/LGRS.2022.3198681.
4. S. Gao, J. M. Liu, Y. H. Miao and Z. J. He, "A High-Effective Implementation of Ship Detector for SAR Images," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4019005, doi: 10.1109/LGRS.2021.3115121.
5. H. Li, L. Deng, C. Yang, J. Liu and Z. Gu, "Enhanced YOLO v3 Tiny Network for Real-Time Ship Detection From Visual Image," in IEEE Access, vol. 9, pp. 16692-16706, 2021, doi: 10.1109/ACCESS.2021.3053956.
6. M. -D. Li, X. -C. Cui and S. -W. Chen, "Adaptive Superpixel-Level CFAR Detector for SAR Inshore Dense Ship Detection," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4010405, doi: 10.1109/LGRS.2021.3059253.
7. Z. Hong et al., "Multi-Scale Ship Detection From SAR and Optical Imagery Via A More Accurate YOLOv3," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 6083-6101, 2021, doi: 10.1109/JSTARS.2021.3087555.
8. S. Gao, J. M. Liu, Y. H. Miao and Z. J. He, "A High-Effective Implementation of Ship Detector for SAR Images," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4019005, doi: 10.1109/LGRS.2021.3115121.
9. H. Peng and X. Tan, "Improved YOLOX’s Anchor-Free SAR Image Ship Target Detection," in IEEE Access, vol. 10, pp. 70001-70015, 2022, doi: 10.1109/ACCESS.2022.3188387.
10. Q. Hu, S. Hu, S. Liu, S. Xu and Y. -D. Zhang, "FINet: A Feature Interaction Network for SAR Ship Object-Level and Pixel-Level Detection," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5239215, doi: 10.1109/TGRS.2022.3222636.
11. Topouzelis, K.; Papakonstantinou, A.; Garaba, S.P. Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). Int. J. Appl. Earth Observ. Geoinf. 2019, 79, 175–183.
12. Compa, M.; March, D.; Deudero, S. Spatio-temporal monitoring of coastal floating marine debris in the Balearic Islands from sea-cleaning boats. Mar. Poll. Bull. 2019, 141, 205–214.
13. Themistocleous, K.; Papoutsa, C.; Michaelides, S.; Hadjimitsis, D. Investigating Detection of Floating Plastic Litter from Space Using Sentinel-2 Imagery. Remote Sens. 2020, 12, 2648.
14. Cheng, Y.; Zhu, J.; Jiang, M.; Fu, J.; Pang, C.; Wang, P.; Sankaran, K.; Onabola, O.; Liu, Y.; Liu, D.; et al. FloW: A Dataset and Benchmark for Floating Waste Detection in Inland Waters. In Proceedings of the Proceedings of the IEEE/CVF International Conference on Computer Vision, Montreal, QC, Canada, 11–17 October 2021 ; pp. 10953–10962.
15. Helinski, O.K.; Poor, C.J.; Wolfand, J.M. Ridding our rivers of plastic: A framework for plastic pollution capture device selection. Mar. Poll. Bull. 2021, 165, 112095.
16. Wang, W.; Gheneti, B.; Mateos, L.A.; Duarte, F.; Ratti, C.; Rus, D. Roboat: An autonomous surface vehicle for urban waterways. In Proceedings of the 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Venetian Macao, Macau, 3–8 November 2019; pp. 6340–6347.
17. Hasany, S.N.; Zaidi, S.S.; Sohail, S.A.; Farhan, M. An autonomous robotic system for collecting garbage over small water bodies. In Proceedings of the 2021 6th International Conference on Automation, Control and Robotics Engineering (CACRE), Dalian, China, 15–17 July 2021; pp. 81–86.
18. Chang, H.C.; Hsu, Y.L.; Hung, S.S.; Ou, G.R.; Wu, J.R.; Hsu, C. Autonomous Water Quality Monitoring and Water Surface Cleaning for Unmanned Surface Vehicle. Sensors 2021, 21, 1102.
19. Chen, J.; Du, C.; Zhang, Y.; Han, P.; Wei,W. A clustering-based coverage path planning method for autonomous heterogeneous UAVs. IEEE Trans. Intell. Transp. Syst. 2021 doi:10.1109/TITS.2021.3066240
20. Jeon, C.W.; Kim, H.J.; Yun, C.; Han, X.; Kim, J.H. Design and validation testing of a complete paddy field-coverage path planner for a fully autonomous tillage tractor. Biosyst. Eng. 2021, 208, 79–97.
21. Jeon, C.W.; Kim, H.J.; Yun, C.; Han, X.; Kim, J.H. Design and validation testing of a complete paddy field-coverage path planner for a fully autonomous tillage tractor. Biosyst. Eng. 2021, 208, 79–97.
22. Xu, P.F.; Ding, Y.X.; Luo, J.C. Complete Coverage Path Planning of an Unmanned Surface Vehicle Based on a Complete Coverage Neural Network Algorithm. J. Mar. Sci. Eng. 2021, 9, 1163.
23. Lebreton, L.C.; Van Der Zwet, J.; Damsteeg, J.W.; Slat, B.; Andrady, A.; Reisser, J. River plastic emissions to the world’s oceans. Nat. Commun. 2017, 8, 1–10.
24. Peng, Y.; Yang, Y.; Cui, J.; Li, X.; Pu, H.; Gu, J.; Xie, S.; Luo, J. Development of the USV ‘JingHai-I’and sea trials in the Southern Yellow Sea. Ocean Eng. 2017, 131, 186–196.
25. Ruangpayoongsak, N.; Sumroengrit, J.; Leanglum, M. A floating waste scooper robot on water surface. In Proceedings of the 2017 17th International Conference on Control, Automation and Systems (ICCAS), Ramada Plaza, Jeju, Korea, 18–21 October 2017; pp. 1543–1548.
26. Cabreira, T.M.; Di Franco, C.; Ferreira, P.R.; Buttazzo, G.C. Energy-aware spiral coverage path planning for uav photogrammetric applications. IEEE Robot. Autom. Lett. 2018, 3, 3662–3668. [CrossRef]
27. Villa, J.; Aaltonen, J.; Koskinen, K.T. Path-following with LiDAR-based obstacle avoidance of an unmanned surface vehicle in harbor conditions. IEEE/ASME Trans. Mechatron. 2020, 25, 1812–1820.
28. Wang, H.; Guo, F.; Yao, H.; He, S.; Xu, X. Collision avoidance planning method of USV based on improved ant colony optimization algorithm. IEEE Access 2019, 7, 52964–52975.
29. Kim, H.; Koo, J.; Kim, D.; Park, B.; Jo, Y.; Myung, H.; Lee, D. Vision-based real-time obstacle segmentation algorithm for autonomous surface vehicle. IEEE Access 2019, 7, 179420–179428.
30. Steccanella, L.; Bloisi, D.D.; Castellini, A.; Farinelli, A.Waterline and obstacle detection in images from low-cost autonomous boats for environmental monitoring. Robot. Auton. Syst. 2020, 124, 1–11.

31. Guardeño, R.; López, M.J.; Sánchez, J.; Consegliere, A. AutoTuning environment for static obstacle avoidance methods applied to USVs. J. Mar. Sci. Eng. 2020, 8, 300.
32. Li, Y.; Tian, L.; Li, W.; Li, J.; Wei, A.; Li, S.; Tong, R. Design and experiments of a water color remote sensing-oriented unmanned surface vehicle. Sensors 2020, 20, 2183.
33. Ferri, G.; Manzi, A.; Fornai, F.; Ciuchi, F.; Laschi, C. The HydroNet ASV, a small-sized autonomous catamaran for real-time monitoring of water quality: From design to missions at sea. IEEE J. Ocean. Eng. 2015, 40, 710–726.
34. Madeo, D.; Pozzebon, A.; Mocenni, C.; Bertoni, D. A low-cost unmanned surface vehicle for pervasive water quality monitoring. IEEE Trans. Instrum. Meas. 2020, 69, 1433–1444.
35. Cao, H.; Guo, Z.;Wang, S.; Cheng, H.; Zhan, C. Intelligent wide-area water quality monitoring and analysis system exploiting unmanned surface vehicles and ensemble learning. Water 2020, 12, 681.
36. Cryer, S.; Carvalho, F.;Wood, T.; Strong, J.A.; Brown, P.; Loucaides, S.; Young, A.; Sanders, R.; Evans, C. Evaluating the sensor equipped autonomous surface vehicle C-worker 4 as a tool for identifying coastal ocean acidification and changes in carbonate chemistry. J. Mar. Sci. Eng. 2020, 8, 939.
37. Kong, S.; Tian, M.; Qiu, C.; Wu, Z.; Yu, J. IWSCR: An intelligent water surface cleaner robot for collecting floating garbage. IEEE Trans. Syst. Man Cybern. Syst. 2020.
38. Wang, Z.; Liu, Y.; Yip, H.W.; Peng, B.; Qiao, S.; He, S. Design and hydrodynamic modeling of a lake surface cleaning robot. In Proceedings of the 2008 IEEE/ASME (AIM) International Conference on Advanced Intelligent Mechatronics, Xian, China, 2–5 July 2008; pp. 1343–1348.
39. Ruangpayoongsak, N.; Sumroengrit, J.; Leanglum, M. A floating waste scooper robot on water surface. In Proceedings of the 2017 17th International Conference on Control, Automation and Systems (ICCAS), Jeju, Korea, 18–21 October 2017; pp. 1543–1548.
40. Li, X.; Tian, M.; Kong, S.;Wu, L.; Yu, J. A modified YOLOv3 detection method for vision-based water surface garbage capture robot. Int. J. Adv. Robot. Syst. 2020, 17, 1–11.
41. Bai, J.; Lian, S.; Liu, Z.; Wang, K.; Liu, D. Deep learning based robot for automatically picking up garbage on the grass. IEEE Trans. Consum. Electron. 2018, 64, 382–389.
42. A. Roshini and H. Anandakumar, “Hierarchical cost effective leach for heterogeneous wireless sensor networks,” 2015 International Conference on Advanced Computing and Communication Systems, Jan. 2015, doi: 10.1109/icaccs.2015.7324082.
43. A. Haldorai and A. Ramu, Eds., “Cognitive Social Mining Applications in Data Analytics and Forensics,” Advances in Social Networking and Online Communities, 2019, doi: 10.4018/978-1-5225-7522-1.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: