Underwater Debris Detection and Classification Using Deep Learning Models

By

Maghfoor Ahmad Siddiqi

(Registration No: 00000329455)

Master of Science in

Bioinformatics

Supervisor: Dr. Ishrat Jabeen.

School of Interdisciplinary Engineering & Sciences

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

(2024)

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS Thesis written by Mr / Ms__Maghfoor ahmad siddiqi____ (Registration No. __000000329455_), of _____SINES____ (School/College/Institute) has been vetted by undersigned, found complete in all respects as per NUST Statutes/ Regulations/ Masters Policy, is free of plagiarism, errors, and mistakes and is accepted as partial fulfillment for award of Masters degree. It is further certified that necessary amendments as point out by GEC members and evaluators of the scholar have also been incorporated in the said thesis.

Signature: ____________________

DR ISHRAT JABEEN
Professor
School of Interdisciplinary
Engineering & Sciences
NUST Sector H-12 Islamabad

Name of Supervisor _______Dr.Ishrat jabeen______

Date: 21-08-2024

Signature (HOD): ____________________

Date: 26-8-2024

Dr. Fouzia Malik
HoD Sciences
Professor
SINES NUST Sector H-12
Islamabad

Signature (Dean/ Principal) ____________________

Principal SINES

Date: 27/08/2024

Dr. Mian Ilyas Ahmad
HcD Engineering
Professor
SINES - NUST, Sector H-12
Islamabad

2

AUTHOR'S DECLARATION

I **Maghfoor Ahmad Siddiqi** hereby state that my MS thesis titled "**Under Water Debris Detection And Classification Using Deep Neural Network Models**…." is my own work and has not been submitted previously by me for taking any degree from National University of Sciences and Technology, Islamabad or anywhere else in the country/ world.

At any time if my statement is found to be incorrect even after I graduate, the university has the right to withdraw my MS degree.

Name of Student: _Maghfoor Ahmad Siddiqi______

Date: ______________27-08-2024_______________

DEDICATION

I dedicate this thesis to my mother, and my late father their continuous support and courage is what leads me to complete this master's program.

ACKNOWLEDGEMENTS

I am deeply grateful to Almighty Allah for providing me with this incredible opportunity to achieve my academic goals. I sincerely appreciate all my instructors who imparted knowledge and guidance throughout my pursuit of an MS degree. In particular, I am immensely grateful to my research supervisor Professor Dr. Ishrat Jabeen, for her valuable guidance and unwavering support throughout my research project. I am also thankful to my research guidance committee member, Dr Muhammad Tariq Saeed and Dr. Maqsood ur rehman kiani, for their insightful comments and encouragement. I would also like to acknowledge skilled engineers and assistants at the SINES labs for their technical support.

Maghfoor Ahmad Siddiqi

TABLE OF CONTENTS

AUTHOR'S DECLARATION **3**

DEDICATION **4**

ACKNOWLEDGEMENTS **5**

TABLE OF CONTENTS **6**

LIST OF TABLES **9**

LIST OF FIGURES **10**

LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS **11**

Chapter 1 .... **13**

1 **Introduction**: **14**

1.1 Underwater debris: 14

1.2 Types of underwater debris: 15

1.2.1 Plastics: 15

1.2.2 Glass: 16

1.2.3 Metal: 16

1.2.4 Ropes and fishing nets: 16

1.3 Sources of underwater debris: 17

1.4 The great pacific garbage patch: 18

1.5 Effects of underwater debris: 19

1.6 Removal of underwater debris: 20

1.6.1 Manual removal: 20

1.6.2 Mechanical removal: 21
1.6.3 Sonar and imaging systems: 21
1.7 Deep learning and underwater debris detection: 21
1.7.1 Deep learning: 21
1.7.2 Underwater debris detection by deep learning: 22
1.8 Problem statement: 23
1.9 Objectives of the study: 23
Chapter 2 24
2 Literature Review: 25
2.1 Previously published underwater debris datasets and applications: 25
2.2 Under water debris dataset classes: 30
Chapter 3 35
3 Methodology 36
3.1 Data collection and preprocessing: 37
3.2 Model architechture: 39
3.3 Evaluation metrics: 41
3.3.1 Confusion matrics: 41
3.3.2 Accuracy: 42
3.3.3 Precision: 42
3.3.4 Recall: 43
3.3.5 F1-score: 43
3.4 Model testing: 43
Chapter 4 45
4 Results: 46
4.1 Performance of the proposed model: 46
4.2 Model prediction on unseen data: 49

Chapter 5 .... **51**

5 Discussion: **52**

Chapter 6 .... **53**

6 Conclusions: **54**

Chapter 7 .... **55**

7 References: **56**

LIST OF TABLES

Table 2.1 Review of literature depicting published underwater debris data................................ 33

Table 3.1 Classes and No. of images of proposed dataset... 37

Table 3.2 Learning parameters of proposed vgg16 model 41

Table 4.1 Final metrics of proposed vgg16 model 46

Table 4.2 Classification summary of vgg16 model 47

LIST OF FIGURES

Figure 1.1 under water debris present in sea 17

Figure 1.2 The great pacific garbage patch 19

Figure 3.1 Experimental work flow 36

Figure 3.2 Under water debris data 38

Figure 3.3 Custom vgg16 model training on proposed data 40

Figure 3.4 Sample test data for model prediction 44

Figure 4.1 Confusion matrix of proposed vgg16 model 48

Figure 4.2 Accuracy and loss curve of vgg16 model 48

Figure 4.3 Models prediction on test image 1 49

Figure 4.4 Model prediction on test image 2 50

LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

AUVs	Autonomous Underwater Vehicles
SDG	Sustainable Development Goals
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
JAMSTEC	Japan Agency for Marine Earth and Science Technology
ROVs	Remotely Operating Vehicles
CNN	Convolutional Neural Network
GANs	Generative Adversarial Networks

ABSTRACT

Debris present inside water poses significant impacts on under water ecosystems along with living organisms thriving in them. In order to address the issue of water pollution and environmental hazards, detection and removal of this growing underwater debris is utmost need of the present times. Therefore, this study explores the application of deep neural network model specifically pretrained vgg16 for detection and classification of underwater debris. Additionally, the current study presents a comprehensive locally collected under water debris images dataset for the detection and classification of debris in local underwater environment is also proposed. The proposed custom vgg16 model performs well in detection and classification of underwater debris with an accuracy of 84%. Moreover, this model is effectively proficient in detecting plastic debris present inside water environment. Furthermore, the model's strength was authenticated through testing on unseen underwater debris images, showcasing its image detection potential for real underwater ecosystem deployment. This study adds to the progression of automatic underwater detection systems, proposing a viable tool for environmental mitigation.

CHAPTER 1

INTRODUCTION

1 Introduction:

1.1 Underwater debris:

Underwater debris is one of the growing threats for the ecosystem. Seas, oceans and other freshwater bodies are continuously being polluted by man-made debris dumped in to these water bodies endangering coastal ecosystem and habitat [1]. In 2016 it was estimated that approximately 23 million metric tons of waste material consisting of plastics and other products entered the aquatic ecosystem from around the world [2]. Dumping, container spills, litter washed into storm drains and waterways, and wind-blown landfill waste all contribute to this issue. This rising water pollution has led to severe negative impacts, including discarded fishing nets trapping animals, the formation of massive patches of plastic debris in the ocean, and increasing levels of contaminants in the food chain [3]. It is often happening many marine animals mistakenly consume plastic or other trash material just because they look similar to some sort of marine animal or plant [4]. Moreover, some type of plastic debris in the ocean degrade and become micro plastics, which are regarded as small pieces of plastics ranging from 0.3 to0.5 millimeters in size. These micro plastics proved to be hazardous for marine animals as they got ingested and deposited in the guts of these marine animals and eventually killed them [5]. Conversely even a biodegradable plastic which is designed in a way to degrade itself over the time when exposed to surface heat, lost its ability to biodegrade in cold seawater environments [6]. Micro plastics also causes genetic damage to marine animals as it absorbs certain hydrocarbon compounds which are detrimental towards reproductive health of marine animals when consumed by them [7]. There are many types of underwater debris such as plastics, glass, tin, cans, metallic products, containers, household items, and paper like product, but significantly plastics outnumbered all other types of underwater debris. Almost 75%

of all marine debris is plastic, which contaminates habitats from the farthest regions of Antarctica to the equatorial belt of earth and from the coastal regions to the deepest parts of oceans [8]. Marine trash or underwater debris accumulates in large parts of oceans usually in the middle called gyres. There is one such large patch of underwater debris containing plastics and other trash materials known as great pacific garbage patch which is present in north Pacific Ocean [9]. In Southern Ocean gyres, where diverging surface currents catch and hold floating garbage, there are very large quantities of floating micro plastics, according to oceanic models and environmental data [10]. This issue of marine plastic pollution and underwater debris is growing at an enormous rate which needs human attention in order to devise mitigation strategies [11].

1.2 Types of underwater debris:

There are several types of debris or persistent trash materials which could makeup underwater debris which are as follows.

1.2.1 Plastics:

One of the most abundant type of marine debris is plastics whether it is macro plastic or micro plastic. An estimated 86 million tons of plastic underwater debris was predicted to be present in the entire world's oceans, as reported by a study at the end of 2013 assuming that 1.4 percent of all plastics made worldwide between 1950 and 2013 ended up being in the ocean [12].According to the United nation Oceans Conference held in 2017 it was proposed that oceans will contain more weight of plastics then fishes by 2050 [13].Although there are wide variety of plastics present in underwater environment of every sort. Some of the most common examples are plastic bags, rubber, tires, bottles, derelict fishing gears and packaging as shown in figure 1.

1.2.2 Glass:

With increasing human population and glass manufacturing and usage is also increased, due to which glass pollution in water bodies is at rise. Although plastic is in abundance in water debris, glass is equally harmful for marine ecosystems. Glass debris particularly is heavy and directly got submerged in floor of seas or any water body, making it completely invisible for humans. More over glass broken down to small particles are harmful for animals and fishes incase if they feed upon them or got injured from them. Glass found in under water debris is mainly glass bottles, fishing gears and discarded medical products made exclusively with glass [14].

1.2.3 Metal:

Metallic products are also present in marine and water environments. Mainly tin cans, metal containers which are dumped intentionally or in intentionally in seas, metal drums, shipwrecks and fishing gears of metal grade are found in underwater debris. Almost 1,382 shipping containers are lost in seas each year according to the World Shipping Council [15]. Lost shipping containers when starts to decay pose negative effects on the surrounding environment.

1.2.4 Ropes and fishing nets:

One of the most prominent types of underwater debris are ropes and fishing nets. Both of these can be of metallic nature, plastic or made up of cotton materials. These are often termed as "ghost nets" [18]. Ghost nets are abandoned fishing nets left in the sea after fishing activity. Even after being left in the sea, these fishing nets don't stop catching marine animals. Sea turtles, fishes, sea lions and even crabs got entangled in these ghost fishing nets. According to a study approximately 4368 crabs got trapped in the impact lifetime of a net causing a huge loss of $19,656 for the fishing industry also [19].

Figure 1.1 under water debris present in sea

1.3 Sources of underwater debris:

Underwater debris can accumulate from different sources such as human recreational activities in coastal areas and from land based human activities which produce debris [20]. Most of the underwater debris comes directly from maritime activities. Global shipping business contribute heavily to this issue through left off containers, cargo spills and dumping of plastic packaging materials. Discarded solid waste from ships, including glass, metal and plastics, also increase underwater debris. Moreover, the world's fishing industry is a prominent contributor which creates marine debris by leaving fishing nets and fish catching gears in the open seas. These fishing gear could cause entanglement of marine animals, damage the coral reefs, and disturb the underwater ecosystems. Human entertainment activities may also play a role, with litter disposal from boats, fishing products, and other equipment regularly ending up in the water [21]. surface runoff is a major land-based source of underwater debris. Most of the debris comes in water bodies though storm water which carries trash from urban settlements and industrial zones. Rivers and streams act as a means of transportation for debris. Leakage from sewages and clogged water channels also contribute towards underwater debris [22]. Calamities such as, typhoons, hurricanes, floods and tsunamis can cause huge incorporation of debris into marine environments. High pressure winds due to these hurricanes carry debris from coastal and city areas into the seas. Flash floods can introduce a tremendous load of solid debris, including plastic bags, household items, and even construction materials, into water bodies [23]. Underwater plastic pollution is a prevalent issue, with growing presence of disposable plastics, packaging materials and micro plastics. These materials can stay in the marine ecosystem for hundreds of coming years, creating long-term hazards towards marine life and ecosystems [24]. Infrastructure development and construction activities around the coastal regions generate debris, including concrete, metal structures and wood waste. This debris can enter the marine environment through rivers, streams or direct disposal, escalating underwater pollution [25]. One of the main sources of metallic underwater debris are incidental sinking of ships and aircrafts, with abandoned vessels and their shipping containers adding to the underwater pollution load. These broken wrecks can release hazardous materials and contribute to the degradation of marine habitats over time [26].

1.4 The great pacific garbage patch:

The Great Garbage Patches are huge regions of the ocean where plastics, derelict fishing gears, and other marine debris are floating in the water. They came into existence by ocean currents rotating in a specific order and are called “gyres” [27]. It is reported that at least 76000 tons of plastics are floating in 1.6 million km of ocean. Almost 92% of the patch consists of larger plastic which are not converted to micro plastics, but still mariners and divers collected small fragmented plastics from the patch. The plastic in the patch is so widely dispersed that this large patch is not even captured from space satellites [28]. Despite plastic removal from garbage patch it is rapidly increasing in size and more plastic is accumulating. This great pacific garbage patch is posing continuous threat to marine ecosystem [29].

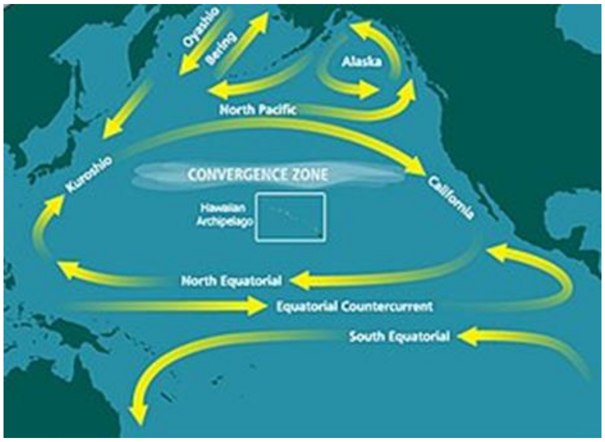

Figure 1.2 The great pacific garbage patch

1.5 Effects of underwater debris:

Underwater debris, in particular plastic, glass, metallic objects and other waste materials impose persistent threats to the ecosystem. It is physically damaging for underwater animals as they can get entangled in between the fishing nets and can also get injured by any sharpened edges of metallic or glass objects [30]. Marine animals may mistakenly ingest small plastics known as micro plastics, these can hinder digestive process and causes starvation, moreover internal injuries can also happen. The chemicals in micro plastics often leach into the tissues of these animals which also become part of the food chain and eventually these plastics enter the human body when these animals are consumed [31]. Underwater debris also contributes towards habitat destruction of marine animals as it can hinder coral reefs and other underwater plants ecosystem and their life cycle, consequently marine animals that are dependent upon these coral reefs and plants for their shelter and food also get affected negatively [32].As underwater debris disintegrate in water, it can release chemicals that are toxic in nature and contaminate sea bed and water, affecting the health and life cycle of underwater organisms[33].Underwater debris not only damages the underwater ecosystem but also hinders economic activities like tourism, fishing, and shipping.it makes hurdle for cargo ships and fishing boats, aesthetic beauty of seashore or rivers also gets reduced. An estimated loss of about 197 billion $ is reported due to underwater debris [34]. A substantial impact of underwater debris is posed on climate. Underwater plastic debris which are fossil fuel based when degraded in water emits certain greenhouse gases which are harmful for climate change and increase global warming issue [35].

1.6 Removal of underwater debris:

Underwater debris is a pervasive challenge for the underwater ecosystem. Removal of underwater debris is crucial for preserving the underwater ecosystem ensuring safety of marine animals. There are various methods for underwater debris removal some of them are:

1.6.1 Manual removal:

Experienced divers can manually gather debris from underwater environments, especially in areas like coral reefs which are sensitive and prone to danger of being damaged. This manual removal is effective for limited scale cleanups and sensitive operations [36].

1.6.2 Mechanical removal:

. Use of Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) can be used to detect and collect underwater debris is a more efficient way of cleaning underwater debris as it is less dangerous and does not require manual labor. An efficient artificial intelligence framework is however needed to operate, detect and collect underwater debris [37].

1.6.3 Sonar and imaging systems:

Using sonar images, deep sea imagery, and other advanced computer vision technologies to locate and observe debris concentration regions for targeted cleanups is comparatively new and less labor intensive [38].

1.7 Deep learning and underwater debris detection:

1.7.1 Deep learning:

Deep learning, a subfield of artificial intelligence, involves training deep neural networks on preprocessed data to perform computationally vigorous tasks like speech and image recognition, autonomous decision-making, and natural language processing. These models, influenced by the human brain, consist of multiple layers of neurons that can learn hierarchical features from large datasets. Key architectures in deep learning includes convolutional neural networks (CNNs) for image classification or detection, generative adversarial networks (GANs) for data generation and recurrent neural networks (RNNs) for sequential data. Deep learning has significant benefits in the fields of image recognition, healthcare, and autonomous computing systems [39].

1.7.2 Underwater debris detection by deep learning:

Finding and locating underwater debris by utilizing human labor is an arduous task, which requires a considerable amount of preplanning and finance. Determining underwater debris manually is also time consuming and has limited area coverage. However more efficient way of detecting underwater debris is through image recognition, which can automatically detect underwater debris with the help of deep learning algorithms incorporated in autonomous underwater vehicles (AUVs) [40]. Removal of underwater debris with AUVS or underwater robots is effective as it can explore regions where otherwise divers cannot go easily and involves minimal risk, also these systems can remove underwater debris by collecting them and eventually discarding them out of the water environment [41]. Detecting underwater debris is a challenging operation because debris comes in any shapes and colors, it can be intact or it can be a broken one. In each case recognizing debris specifically under water is difficult. Here or in order to learn more features in an image which contain debris, deep learning comes into play as it can better learn complex features in an image then machine learning alone [42]. As deep learning models require a large amount of data to learn the feature maps from the image, underwater debris detection through deep learning is possible only when there is a large amount of image data available [43]. However, this particular problem of underwater debris detection has a data scarcity issue. There is limited amount of data available online while the online datasets are region specific and are incapable of true representation of underwater debris elsewhere in the world [44]. For example, the image dataset of underwater debris collected from the sea near japan is different from the dataset collected near the Indian ocean.so in order to fully utilize the applicability of deep learning models truly representative underwater debris data is needed.

1.8 Problem statement:

Under water debris is one of the major environmental concerns in Pakistan and globally. Due to high population burden, the water bodies like rivers, dams, streams and marine areas of Pakistan are at risk of being dumping reservoir of plastic and other sorts of debris. Therefore, in an attempt to make these water bodies clean, mitigation steps have to be taken. Manually visualization of underwater debris with naked eye or searching through diving operations, proved to be time consuming and labor intensive. This issue could be solved with the help of using autonomous underwater vehicles AUVS by incorporation of deep learning models. However, these deep learning models requires large data. under water debris dataset is not available in large quantity, in order to build effective framework that can detect underwater debris with help of AUVs, a large diverse underwater debris dataset is in need.

1.9 Objectives of the study:

Following are the objectives of the prospective study

- To collect the underwater debris data from different water bodies of Islamabad.
- To develop a predictive deep learning model by utilizing the dataset.

CHAPTER 2

LITERATURE REVIEW

2 Literature Review:

2.1 Previously published underwater debris datasets and applications:

Underwater debris is an emerging issue globally as well as in local scenarios. Coastal seabed of Karachi is polluted with more prevalent type of plastic debris such as single use plastic bags and polystyrene as reported in a study [45]. However, the detection and removal is a challenging task, currently it requires manual labor and divers to identify and collect waterbody and can be monitored and observed from ships for collection [46]. Latest techniques that are used to detect and remove the underwater debris includes under water robots, autonomous vacuums (AV), vessel with nets (VN) etc. which are equipped with proper detection and removal systems [47]. In order to develop an efficient detection system, employing deep learning frameworks, a large labeled dataset is a foremost requirement [48]. [49] trained binary and a multiclass classifier for underwater household debris, for which they collected data of Forward-Looking Sonar (FLS) images of submerged debris generated by ARIS Explorer 3000 FLS, with the help of AUV (Autonomous underwater vehicle). 2000 images were captured inside a water tank containing different classes of debris objects. The whole data set was split up into training, validation and testing set in a ratio of 70%, 15%, 15% respectively. The model proposed by this study doesn't classify deformed debris very well. A study conducted by [50] to detect the underwater fishing nets abandoned by fisherman in the sea. The study utilized an underwater robot to make image data in a laboratory in an underwater environment. This data includes 6600 images: the training set consists of 6200 images and the other 400 images were used as the test set. The images were captured with different viewing angles so that every dimension of the objects is recorded. The brightness and clarity of various images has also been adjusted in order to imitate different water quality scenarios. The dataset was generated by capturing videos of marine plastic in various locations in California, including South Lake Tahoe, Bodega Bay, and San Francisco Bay. The videos exhibit significant diversity in quality, depth, and visibility to accurately depict the challenging conditions of marine environments. Following recording, a manual identification process was undertaken to select still images featuring complex object detection scenarios such as illumination variations, noise, and occlusion. Each chosen image underwent annotation for object detection using deep learning models. This curation method aimed to ensure that the dataset closely mirrors real-world conditions. To enhance the dataset's geographical representation, images were also obtained from datasets created by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC). resulting in a final dataset comprising 3200 images.

Another study also worked with the J-EDI dataset of marine debris made by the Japan Agency for Marine Earth Science and Technology (JAMSTEC). This data contains images of marine debris dated back to 1982. The training data was extracted from videos captured between 2000 and 2017. Each video was sampled at a rate of 3 frames per second. overall 240,000, from which a final training dataset containing images up to 5,720 was made. Training images are manually labelled using a free tool label image and kept at 480*320 [51]. Under water debris data is not readily available so a work proposed a method to cope with the data scarcity of underwater plastic debris by using a generative approach to generate a synthetic new data from original data. The original data was sourced from the J-EDI dataset available online. From this data, 775 images of plastic bags and a total of 283 images of plastic bottles were collected. After augmenting theses horizontally, vertically, and rotating them about 90 degrees, the final data that was used for generative modelling includes about 3,000 images of plastic bags and 1,000 images of plastic bottles. Another data set of about 4,405 images of fish from the QUT fish dataset was also collected, from which 3,000 images were randomly selected for the purpose of training and testing multiclass classifier. 271 images of underwater scenes without any objects were also collected and also got them augmented according to the method described above, this makes them about 3,000 images of underwater scenes [52]. [53] gathered the data set of deep sea garbage from Japan Agency for Marine-Earth Science and Technology (JAMSTEC). approximately 10,000 images are extracted from videos of the above mentioned dataset and labelled with labeling labelling tool eventually named as 3D-dataset. There are serious inconsistencies within classes and also similarities are observed between classes. The plastic class is dominant among all classes whereas the glass class has the lowest number of examples in the dataset. In order to gather image data a study used a towed underwater camera to gather the sea floor marine litter data and collected in a framework called “Integrated information and awareness campaign for the reduction of plastic bags in the marine environment” program (LIFE DEBAG - LIFE14 GIE/GR/0011271)”. This dataset was gathered from Ermoupolis bay in Syros Island, Greece. The recorded videos were timestamped with precise UTC time from GPS fixes, ensuring accurate data. This particular dataset includes a total of 635 image frames extracted from videos with 1920 × 1080 pixels. A total of 1166 litter items were manually identified in the images, and 2D bounding boxes were marked around these items using the Labeling image annotation tool. As the size of the data was relatively small data augmentation was applied to these images. The final augmented data set contains 3910 images also excluded Instances of low image contrast and water turbidity from the video frames data [54]. One study utilized dataset which is sourced from the database of "The Japan Agency for Marine-Earth Science and Technology (JAMSTEC)”, specifically their deep-sea debris database, designed for detecting marine litter objects. This dataset comprises both videos and images of marine debris, providing valuable resources for litter object detection. The dataset consists of 1,918 images [55]. [56] used a deep sea debris database provided by Japan Agency for Marine-Earth Science and Technology (JAMSTEC) in conjunction with additional data from Google Images to make the image dataset for the study of marine debris classification. The dataset underwent manual labelling and validation by a researcher, ensuring thorough scrutiny before using it for classification. The final dataset contains 2395 images categorized into six classes. approximately 20% data was used for final model evaluation from each class and the rest 20% was allocated for training. Music, J.et.al. [57] employed a "three prong" approach by formulating a dataset from internet resources, underwater scenes, and synthetic models. A total of 2,527 images with 3,371 object instances were collected from all these resources. However, among the collected images plastic was more prevalent. Hybrid images, incorporating real underwater backgrounds with synthetic marine litter models, were generated using Blender 2.8 and Python scripts. The hybrid images were mainly generated with use of underwater backgrounds, importing 3D models from the ShapeNetCore database, and calculating projection coordinates for YOLOv3 training eventually forming a marine litter detection database. The dataset was intentionally split into 60%-20%-20% for train-validation-test sets. (Japheth C. Hipolito et. al.) sourced the dataset for the study from the Data Repository for the University of Minnesota (DRUM), precisely the Dataset containing Underwater Trash. A total of 8580 images were collected from the DRUM dataset to be used for training and testing data sets. The train test split was kept 80% and 20% respectively. Zhe Hu et. al. [60] also used a public database for improved object detection models. A total of 2315 images were obtained after sorting out and processing. The dataset comprised 1736 images for training, 552 for verification, and 579 for testing. Also the labels were in .txt text format, with image resolution was set at 416×416 pixels. Premanand Ghadekar et. al. [61] in a conference presented a fast water debris detection model based on yolov5. Approx. 500 images in the data set were reserved for the training set and also 500 for the validation set. training set was increased to about 1000 images by the application of upsampling or data augmentation. the data was labelled with labelimg tool. some of the data augmentation applied on the training data were Dehazing, Min-Max Contrast Stretching, Adaptive Histogram Equalization. Dongliang Ma et.al. [62] performed an experiment by using TrashCan dataset (Hong et al., 2020a) for effective evaluation, sourced from the J-EDI dataset.The dataset has two versions TrashCan-Material and TrashCan-Instance, this dataset includes 7212 underwater trash images consequently 6008 images with 9741 underwater material objects used for training, and 1204 images with 2595 under-water material objects for testing. The TrashCan-Material dataset was splitted into a training set (83%) and a test set (17%) and The TrashCan-Instance dataset followed an 84% train set and 16% test set ratio. Bhanumathi M et. al. [63] scraped some ocean or marine plastic images from kaggle, shutterstock and other resources. Besides this image augmentation was used to increase the dataset. Data augmentation procedures like flipping ,rotating and colour correction are applied in order to simulate marine plastic images. The final dataset includes approximately 4000 images which were splitted into training and test set in 80% and 20% ratio. Manjun Tian et.al. [64] proposed a pruning based yolov4 object detection model for underwater debris identification and utilized an underwater robot to capture images comprising a total of 6,600 images, with 6,200 allocated for the training set and the remaining 400 for validation. These images were taken in a real underwater environment, with different angles, moments, illumination conditions, and relative orientations between the robot and debris objects. Brendan Chongzhi Corrigan et. al. [65] utilized an instance version of Trashcan dataset sourced from JAMSTEC e library of deep sea debris images because of the intra-class variability observed in the material version of this dataset.

The dataset for training was labelled to instance segmentation level and splitted into 80% for training and 20% for validation. Total annotated images used were around 7212.

2.2 Under water debris dataset classes:

Previously, Underwater plastics need some kind of categorization in order to build classification of object detection models. Matias Valdenegro-Toro et. al [66] worked with FLS imagery data of submerged household debris. This data was used to perform two classifications namely a binary classification and a multiclass classification for binary classification obviously two classes are to be worked with and those are “debris” vs “background”. For multiclass classification 6 classes were made of submerged debris namely “metal, glass, paper or cardboard, rubber, plastic and background”. Manjun TIAN et.al. [67] made three classes for the object detection cnn model. These classes include “fishing nets”, “bags” and “ stones”. The purpose of including “stone” class in the project was an intentional move so that the model can detect stones in a real underwater environment too. This is important because an underwater robot needs to be aware of the surrounding environment and plastic within. oceans environment is diversified so the Gautam Tata et.al [68] included all the image data containing plastics into a single class named as “trash_plastic”. The data set is open sourced and available online. Michael Fulton et. al [69] assorted the images data into 3 classes for the trash detection model.namely the three classes were “plastic”, “ROV”and “Bio”. As the name suggests plastic class contains all marine debris or plastic mainly. ROV class was made for all the manmade objects placed intentionally in water, in this case it is the robot which is capturing the images. The BIO class has images of all the natural environments including fish, plants and any biological entity. Michael Fulton et. al [69] wants to classify plastic and ROV from BIO class. Hong, J et.al. [70] used both binary classification and multiclass classification after generating more data from variational autoencoders. For binary classification, two classes, namely “plastic bags”and “plastic bottles,“ are employed. whereas there are 4 classes which include “plastic bottles”, “plastic bags”, “fish” and “ empty” where class “empty” depicts the underwater scenes without any object in it. Bing Xue et.al [72] made seven classes of the training set which is called the 3D- dataset.these classes include metal, glass, fishing net and rope, rubber, cloth, natural debris, plastic. D.V. Politikos et al.[73] In order To streamline the annotation process, big objects made of different materials (wooden, metallic ,plastic) were grouped into a "big object" class, and unidentifiable objects were merged into a new class named "unspecified." The distribution of annotated litter objects revealed plastic bottles and plastic bags as the most frequent classes, while plastic caps and fishing nets were less common. So a total of 11 classes were made for object detection which are as follows:” Unspecified, plastic caps, big objects, tires, small plastic sheets, plastic nets, cans, cups, plastic sheets, plastic bottles, and plastic bags. B. Jalil et. al.[74] distributed across six classes: Glass, Metal, Plastic, Rubber, Other, and No Trash. Manual identification and labelling were performed for each litter object class. (Ivana Marin et.al) in order to make the class distribution among training and test set equal, 20% data from every class was added to the final evaluation set whereas the rest of the 80% data was allocated for model training purposes. (Ivana Marin et.al) made six classes out of the annotated data and these classes were as follows like metal, plastic, rubber, no trash, and other trash. (Josip Musi´c et. al) categorized the marine litter detection dataset mentioned in the proposed study into five classes namely “cardboard, glass, paper, metal, plastic”. The whole dataset contained 2,527 images in total including hybrid images synthetically made from 3d objects scrapped from the internet. Japhet C. Hipolito et. al.[75] split the dataset into two categories namely “bio images” which were 4290 and “non-bio images” consisting of 4290 images.they also selected a small sample of 300 non-bio images. Zhe Hu et. al. [76] conducted a study and employed a single class label named “plastic_trash” for the object detection model. Premanand Ghadekar et. al. [77] in a conference paper used five classes namely plastic bags, plastic bottles, metal cans, and rubber tires. Dongliang Ma et. al [78] used two versions of trashcan dataset namely TrashCan-Material and TrashCan-Instance dataset. in TrashCan-Material classes include ROV, plants, fish, starfish, shells, crabs, eels, animal, trash, fabric, fishing gear, metal, paper, plastic, rubber, and wood. whereas In TrashCan-Instance, classes comprises crabs, eels, animal, fish, shells, starfish, plants, ROV, bags, bottles, branches, cans, clothing, containers, cups, nets, pipes, ropes, snack wrappers, tarps, unknown instance, and wreckages. Bhanumathi M et. al. [79] in order to make a yolov4 and yolov5 model for underwater plastic detection labelled the dataset into single class “plastic. Manjun Tian et. al [80] made an object detection model with focus on three classes which are : fishing nets, stones and plastic bags as these are mostly in abundance in underwater environments. Brendan Chongzhi Corrigan et. al. [81]. performed instance segmentation level categorization of the Trashcan dataset, with 22 classes as follows “ animal_crab, animal_eel, anima_etc, ,animal_fish,animal_shells, animal_starfish, plant, rov, trash_bag, trash_bottle, trash_branch, trash_can, trash_clothing, trash_container, trash_cup, trash_net, trash_pipe, trash_rope, trash_snack_wrapper, trash_tarp,trash_unkown_instance, trash_wreckage. The major gaps in above mentioned researches are lack of available data. Most of the studies above utilized same dataset of marine debris published as deep sea debris database JAMSTEC [82]. Whereas there is a lack of in house localized datasets for underwater debris. So here in this study a locally collected dataset of underwater debris is presented in order to develop systems that can mitigate the issue of underwater debris.

Table 2.1 Review of literature depicting published underwater debris data

Author	Title	Image Dataset	Classes	Algorithms
Ivana Marin et.al	Deep-Feature-Based Approach to Marine Debris Classification	(JAMSTEC) 2395	Glass, metal, plastic, rubber, other trash, and no trash	VGG19, InceptionV3, ResNet50, Inception-ResNetV2, DenseNet121, and MobileNetV2
Harsh Panwar et .al	AquaVision: Automating the detection of waste in water bodies using deep transfer learning	AquaTrash 369 (images)	Glass,Metal,Paper, Plastic	AquaVision model (Reti-naNet)
GautamTata et.al.	A Robotic Approach towards Quantifying Epipelagic Bound Plastic Using Deep Visual Models	Deep trash 3200 (images)	trash_plastic	YOLOv5-S
Jungseok H.et. al	A Generative Approach Towards Improved Robotic Detection of Marine Litter	(jamstec,web) 1,058 (images)	Plastic_bag plastic_bottle	Variational autoencoder, resnet50
Sánchez-Ferrer, A.et. al.	An experimental study on marine debris location and recognition using object detection	Synthetic data, jamstec 990 (images)	17 labels	Mask R CNN (Object detection)

Politikos, D. V. et.al.	Automatic detection of seafloor marine litter using towed camera images and deep learning	Towed underwater camera 3910 (images)	11 catergories	Mask R CNN
Jalil, B.et.al	Comparative analysis of machine learning algorithms for the classification of underwater marine debris	Jamstec data 1918 (images)	Glass,other,rubber,notras -h,metal, plastic	ResNet50, DenseNet,VGG19
Zhou, W.et.al	YOLOTrashCan: A Deep Learning Marine Debris Detection Network	Jamstec data 7212 (images)	Jamstec 9540 (images)	YOLO_TrashCan
Zocco, F.et.al	Towards More Efficient EfficientDets and Real-Time Marine Debris Detection	Trash-ICRA19 1200	Bio, plastic, ROV	EfficientDet
Valdenegro-Toro, M.et al	Submerged Marine Debris Detection with Autonomous Underwater Vehicles	Forward looking Sonar Images 2000	Metal, glass,rubber, paper, plastic, background	CNN based classifier
Fulton, M. et.al	Robotic Detection of Marine Litter Using Deep Visual Detection Models	J-EDI dataset 5,720 (images)	Plastic, ROV, Bio	YOLOv2, Tiny_YOLO, Faster R-CNN, SSD
M, N. B. et.al.	Marine Plastic Detection Using Deep Learning	Kaggle 4000 images	plastic	Yolov4, yolov5

CHAPTER 3

METHODOLOGY

3 Methodology

Detecting underwater debris can be made convenient by adequately using deep learning models. This section will describe the methodology to collect the data followed by data preprocessing, image classification, and model evaluation.

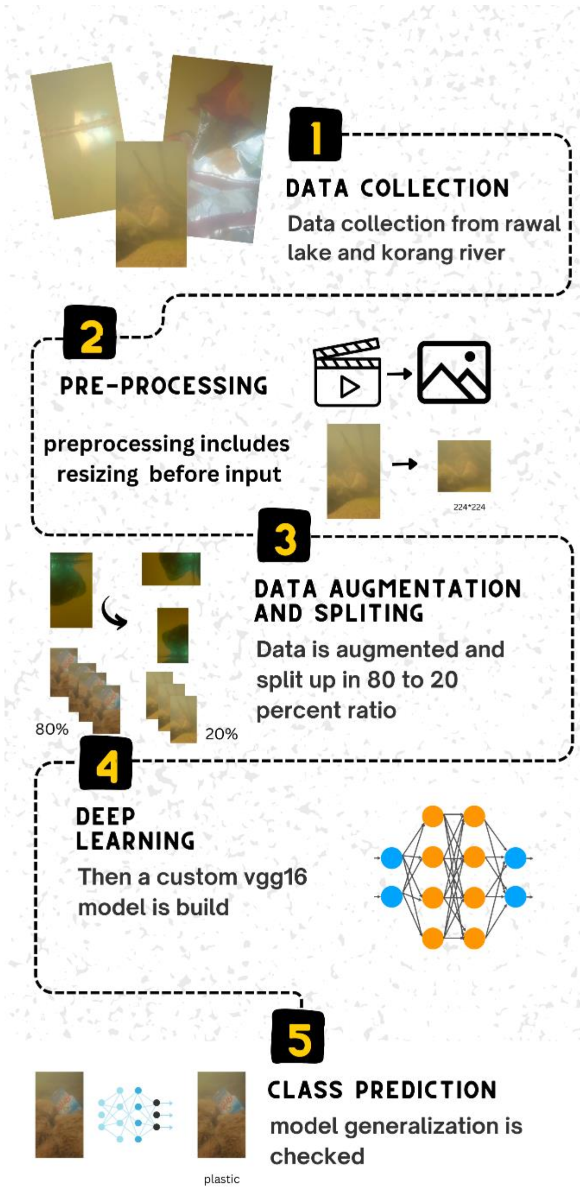

Figure 3.1 Experimental work flow

3.1 Data Collection And Preprocessing:

The problem of underwater debris detection requires a large amount of data in order to build deep deep-learning model. The performance of deep learning model depends upon the quantity and quality of the data which is used to train the model. Furthermore, a diversified dataset comprising various features of the target output, such as colors, different angles and backgrounds of images, strengthens the model's ability to classify images in real-world scenarios accurately. Here in this study underwater debris data was made with the help of mobile device from two different locations of Islamabad city namely Rawal Lake and Korang River at varying depths. Videos of underwater debris present in these two locations were made in 4K resolution. Then video frames were extracted from the collected videos data by a software called video proc converter and sorted for the best-quality frames. Approximately 9,093 image data of underwater debris was made which were divided into four different classes namely plastic, glass, metal, and environment. Class "plastic" contains debris items like plastic bags, disposable glasses, common household plastic products, bottles etc. Class "metal" contains debris materials that are of metallic grade like metal caps, cans, aluminum packaging etc. As far as class "glass" is concerned it includes debris glass products like glass bottles whereas class "environment" does not contain any debris beside it was natural underwater environment of above mentioned locations.

Table 3.1 Classes and No. of images of proposed dataset

Classes	Number of images
Environment	571
Metal	414
Glass	709
Plastic	7,399

After the data collection followed initial preprocessing of video frames extraction, the image data got preprocessed further for training deep learning model. Rescaling was applied to the data so that pixel values set between 0 and 1. After that data augmentation was employed to increase the dataset. Data augmentation steps applied includes horizontal flip and vertical flip as debris objects could be present in any dimension in real underwater scenarios. Image resizing is an important step in preprocessing as deep learning models require consistent image size as input. Underwater debris dataset was resized to 224*224 pixels. The deep learning model requires dataset to be spitted in to training and validation sets, proposed dataset in this study was split up in to 80% training set and 20% validation set. Another set of images approximately 1000 were reserved for testing the trained model on unseen data. This will shows how generalized the deep learning model will be when deployed in real underwater debris detection.

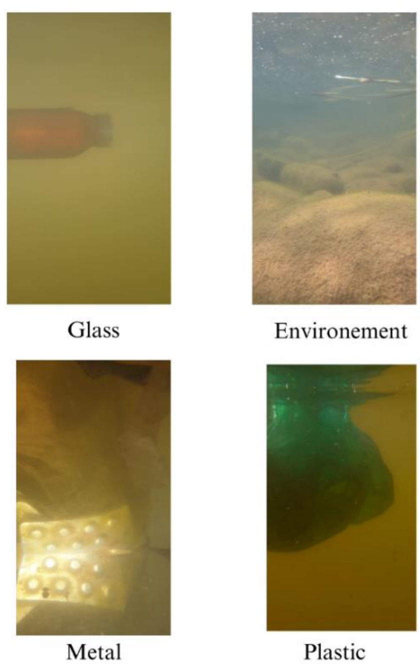

Figure 3.2 Under water debris data

3.2 Model Architechture:

In this study a pretrained vgg16 model is proposed for classification of underwater debris into 4 categories. Vgg16 uses pretrained weights from large image net dataset as shown in figure 3.2. In this way a transfer learning approach is used to train a multiclass classifier. Transfer learning is a technique in deep learning where a pretrained model build for a particular dataset, reused as a starting point for a model for another dataset. In this way pretrained model apply the knowledge learned from large dataset to extract feature from small dataset. Here in this study pretrained vgg16 is used as base model. The top layers are not added in order to add custom classification layers. Moreover, vgg16 layers are frozen to prevent them from being updated during the time of training. Global average pooling 2D layer is added as it reduces the dimensionality of feature maps. The next layer is a fully connected dense layer with 128 neurons and ReLU activation is added. In an attempt to reduce overfitting a dropout of 0.5 is added. Finally, a dense layer is included with softmax activation function which outputs the four class probabilities. Then the model is compiled employing Adam optimizer along with the learning rate of 0.001. As this is a multiclass classification model categorical cross entropy loss function is used. This custom vgg16 model consists a total of 14,780,868 parameters, from these only 66,180 are said to be trainable, this enlightens that the major part of the network employs the fixed, pre-trained VGG16 layers. Afterwards model is trained for 50 epochs. This model was trained on high performance computer (HPC) linux version 4, NVIDIA-SMI Version**:** 510.47.03 along with tesla T4 GPU. Following table no. 3.2 depicts model summary.

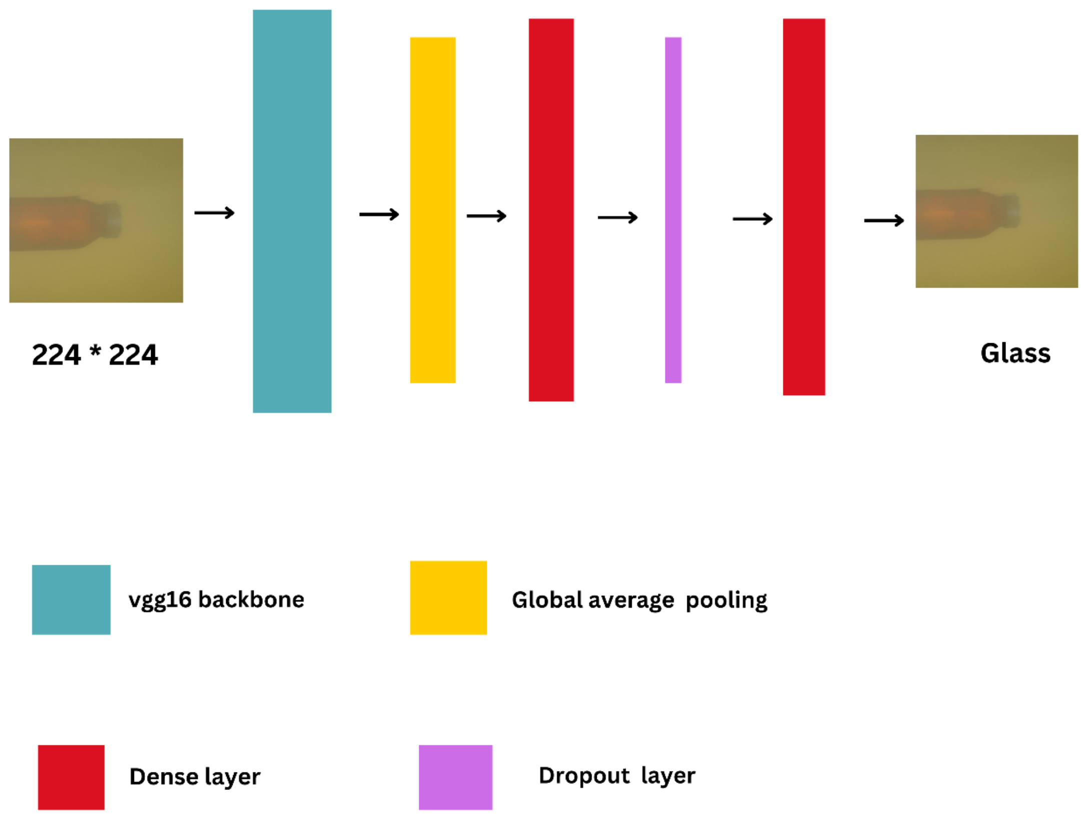

Figure 3.3 Custom vgg16 model training on proposed data

Table 3.2 Learning parameters of proposed vgg16 model

Layer type	Output shape	Parameters
Vgg16 (functional)	(None, 7, 7, 512)	14,714,688
global_average_pooling2d	(None, 512)	0
dense (Dense)	(None,128)	65,664
dropout (dropout)	(None,128)	0
dense_1(Dense)	(None,4)	516
Total parameters	-	14,780,868
Trainable parameters	-	66,180
Non-trainable parameters	-	14,714,688

3.3 Evaluation Metrics:

3.3.1 Confusion matrics:

The evaluation of the performance of deep learning or any classification model is often done by using a confusion matrix. By making use of the confusion matrix, one can acquire a good know how of whether the results are of good quality or bad, as it depicts a table showing the predicted class labels and actual class labels. usually, a confusion matrix consists of four cells: namely true negatives, true positive, false negative, and false positives. In this study images which are correctly classified by model as plastic, glass, metal and environment are true positives TP. whereas when none of the above mentioned classes are identified it is true negative TN. If these four classes are misclassified, then it is false positive FP. however when the model will classify an image being categorized as one of the four classes but in real there is no debris then its false negative FN. By examining the results of the confusion matrix, different performance evaluation parameters such as precision recall and f1 score were calculated to determine the effectiveness of the model in classifying plastic, glass, metal and environment.

3.3.2 Accuracy:

Accuracy is used to measure the overall effectiveness of the model. It is actually the ratio of correctly predicted observations to the total observations.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

3.3.3 Precision:

Precision shows how many of the predicted positive cases were actually positive. Actually Precision is the ratio of correctly predicted positive instances to the total predicted positive instances.

$$Precision = \frac{TP}{TP + FP}$$

3.3.4 Recall:

Recall is also called sensitivity; it tells how many of the true positive cases were correctly identified. Recall is defined as the ratio of correctly predicted positive instances to all the instances in the actual class.

$$Recall = \frac{TP}{TP+FN}$$

3.3.5 F1-score:

It is defined as harmonic mean of precision and recall.it depicts the balance between precision and recall, it is useful when u have to assess a model built with uneven class distribution.

$$F1\ score = \frac{2 * (precison * Recall)}{precision + Recall}$$

3.4 Model Testing:

After the custom vgg16 classifier is trained on the underwater debris dataset, model is tested on another set of unseen data, specifically reserved for prediction purposes. This test data as shown in figure 3.4 is totally unseen by the model during the training. However, this dataset is also sampled from same locations as described previously. The nature of debris items, lighting conditions and background is almost the same.

Figure 3.4 Sample test data for model prediction

CHAPTER 4

RESULTS

4 Results:

4.1 Performance of the proposed model:

The custom vgg16 model trained on the proposed underwater debris dataset performs quite well in prediction of debris in water. The overall models validation accuracy is up to 84% which is quite well in terms of the complex problem the model is solving. It means when model is 84% confident that the image belongs to one of the four classes, when predicting on new data. The model is trained for 50 epochs, as it is performing well in this range of epochs. However, the classification report indicates that the model is able to perform well on “plastic” class in particular, with precision of 0.68 and recall comes out to be 0.93 with F1 score of 0.79 as shown in table 4.2, as it’s a dominating class in the whole dataset. Whereas, other classes like “environment”, “glass” and “metal” indicates less accurate performance metrics, due to class imbalance problem that exists in the data. Training loss is decreased from 0.34 to 0.30, indicating that the model was effectively learning as show in the figure 4.2. The overall F1 score is 0.66.

Table 4.1 Final metrics of proposed vgg16 model

Metric	value
Final loss	0.44
Final accuracy	0.84

Table 4.2 Classification summary of vgg16 model

Class	Precision	Recall	F1-score
Environment	0.05	0.01	0.02
Glass	0.03	0.01	0.02
metal	0.04	0.04	0.04
plastic	0.79	0.89	0.84

Performance of the classification model across all four classes namely environment, glass, metal, can be examined with the help of confusion matrix. The true positives TP are at the diagonal of the confusion matrix. It can be assessed from figure 4.1 that environment class has high number of misclassification, as the model struggles in distinguishing class environment from class plastic, model correctly identifies only 21 images as environment. Model depicts similar behavior of misclassification for metal and glass class also. Whereas custom vgg16 model performs good identification of class plastic, which is justified due to the high number of images in dataset. Despite the overfitting, the model puts out considerably high validation accuracy as shown in the figure 42.

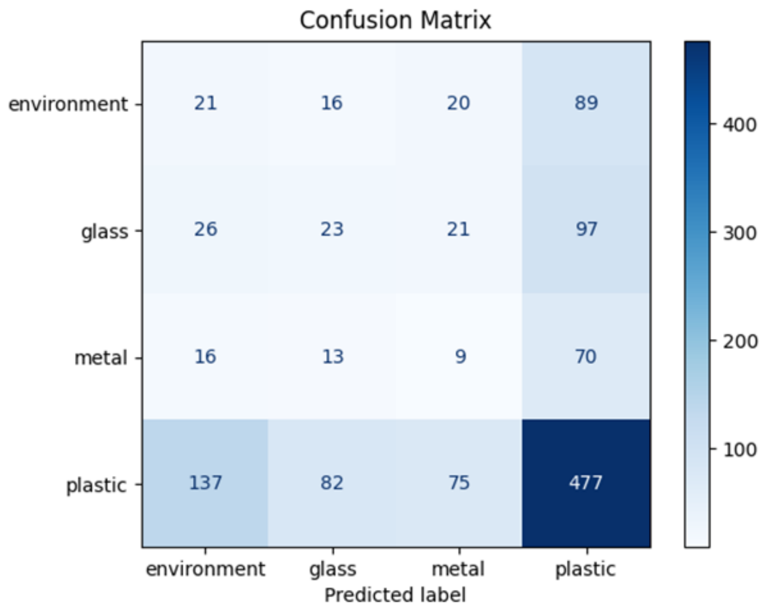

Figure 4.1 Confusion matrix of proposed vgg16 model

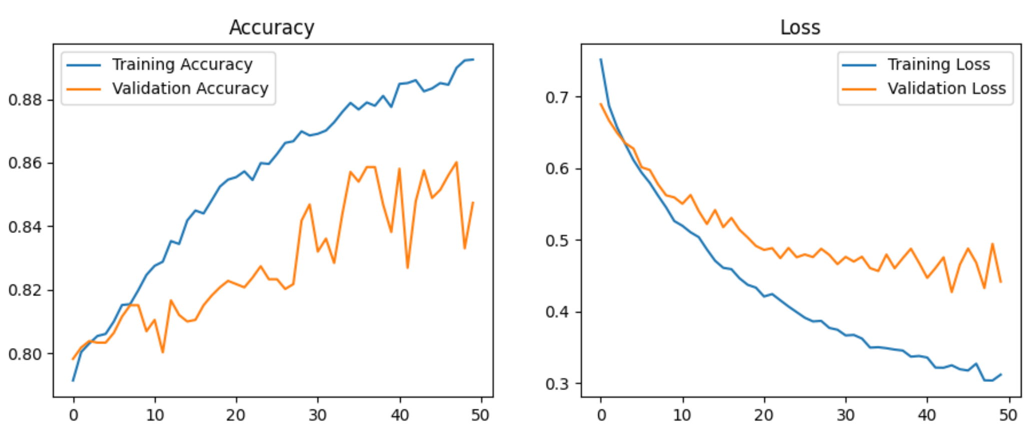

Figure 4.2 Accuracy and loss curve of vgg16 model

4.2 Model Prediction On Test Data:

The proposed custom vgg16 model is able to detect under water debris with an accuracy of 84%. The primary goal of applying deep learning is to make accurate prediction on new unseen raw image. Therefore, in this study the models generalization ability was assessed through testing on unseen images of underwater debris collected from rawal lake and korang river. As shown in the figure 4.3 and 4.4

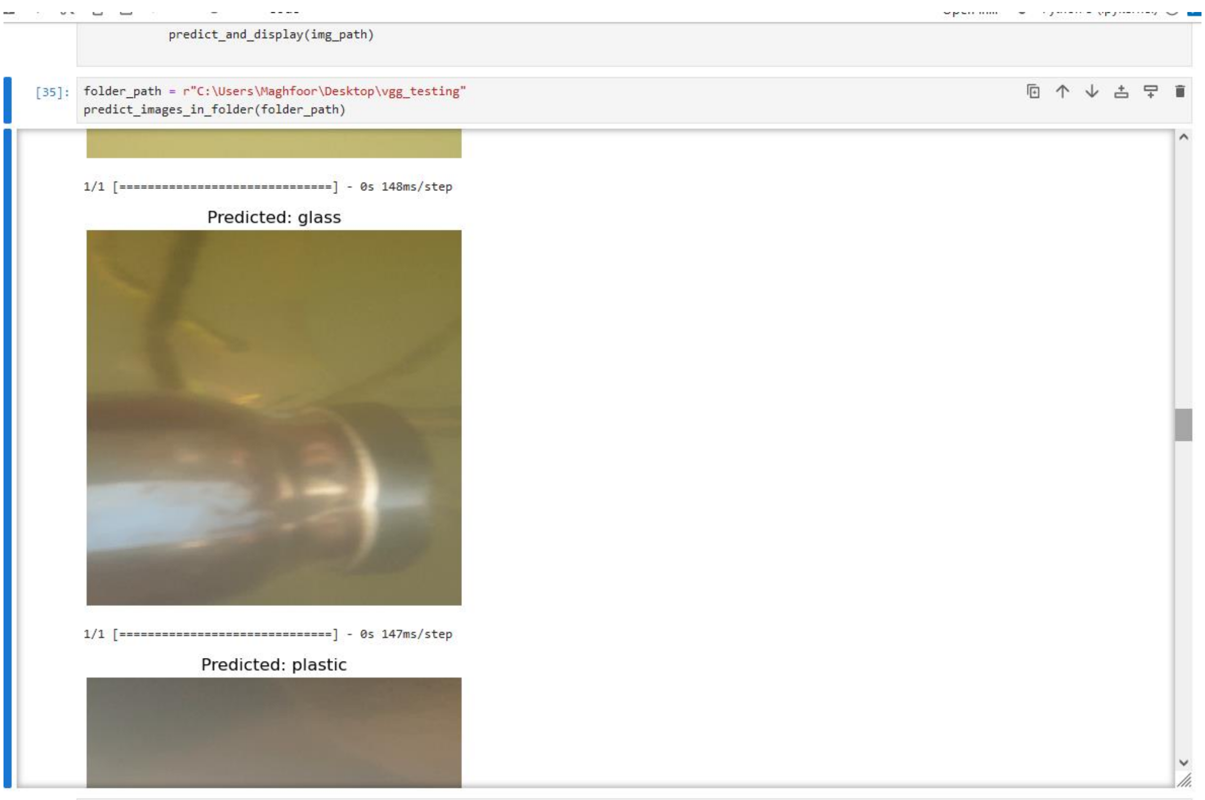

Figure 4.3 Models prediction on test image 1

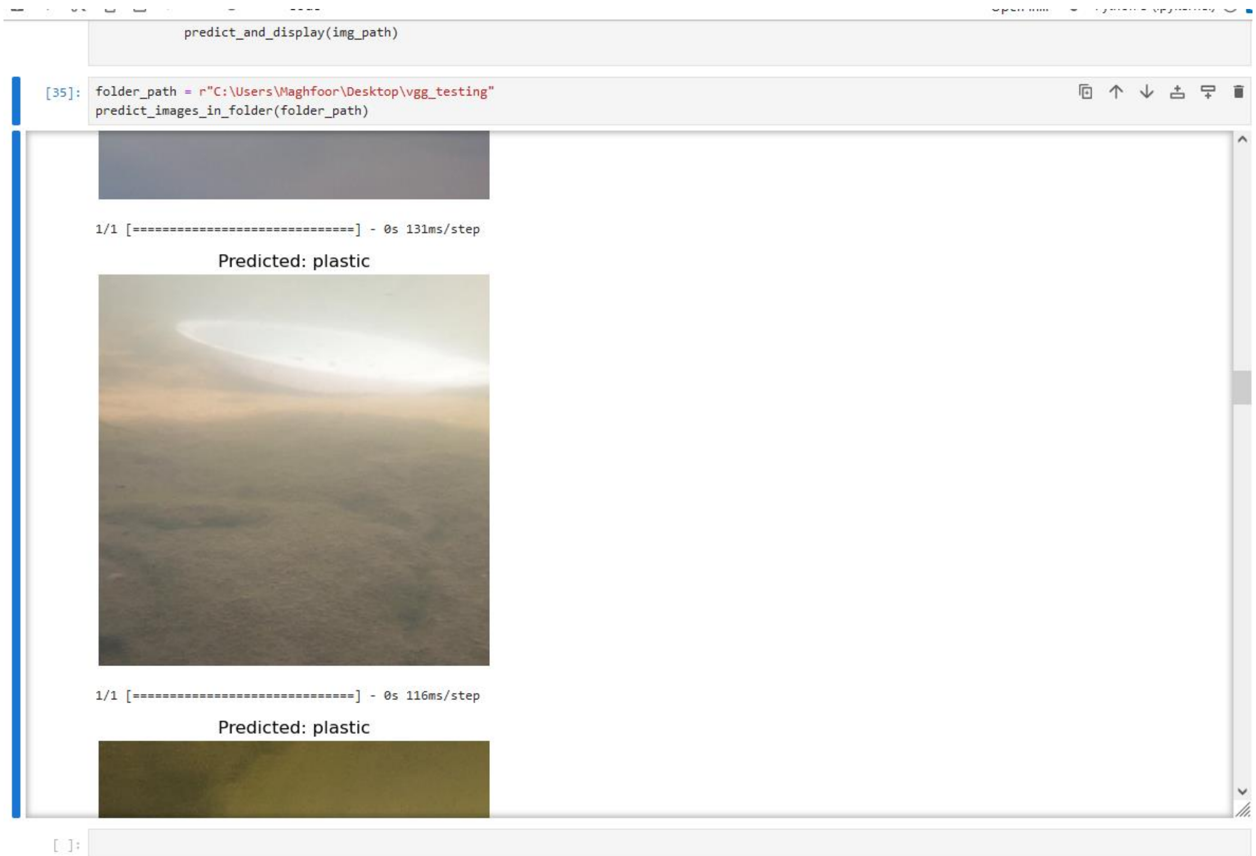

Figure 4.4 Model prediction on test image 2

CHAPTER 5

DISCUSSION

5 Discussion:

In this proposed study, a locally sampled underwater image dataset from different localities is used to train custom vgg16 model, in order to detect and classify 4 different categories. The custom vgg16 model remarkably shows good validation accuracy of up to 84% which is just slightly less than model proposed by J. Musić, [81] which is 85% on publically available dataset. Moreover, the model proposed here in this study is more robust in identification of plastic under water debris due to its dominance in the whole dataset, while remaining classes namely “glass”, “metal” and “environment” depicts relatively less validation accuracies. Owing to the good accuracy of the model, it can be a good tool for detecting underwater debris and in particular plastic debris present inside water bodies as it is more prevalent type of debris found in marine and fresh water environments. Besides the model and datasets limitations of overfitting and class imbalance, the dataset proposed in this study is overcoming the issue of data scarcity discussed by Sánchez-Ferrer, A. [82] as this data is locally collected from real world scenarios. As far as future research directions are concerned it should be focused more on mitigating the above mentioned limitations to increase the models effectiveness and applicability. This includes increasing the size of dataset by collecting images of more diverse type of underwater debris. By increasing the dataset, the issue of class imbalance and overfitting will be reduced. Furthermore, different types of deep learning models which could localize and classify the type of debris should be explored in order to build more efficient automatic underwater debris detection frameworks.

CHAPTER 6

CONCLUSIONS

6 Conclusions:

In conclusion, this study presented an automated deep learning based underwater debris detection framework, which could be used to identify real under water debris effortlessly through any automatic underwater vehicle. A real world underwater debris dataset is proposed in the study which is used to train the vgg16 deep learning model. While the model demonstrates potential for real world underwater debris detection applications, addressing limitations associated to dataset imbalance and model generalization will be essential for advancing its effectiveness across all underwater debris categories. By addressing these challenges, the model can considerably contribute in helping reduction of harmful impacts of debris present in any water body whether it is marine or freshwater ecosystems of Pakistan. More over the findings of this study also address the significance of sustainable development goals (SDG) 14.

CHAPTER 7

REFERENCES

7 References:

1. Sheavly, S.; Register, K. Marine debris & plastics: Environmental concerns, sources, impacts and solutions. J. Polym. Environ.2007, 15, 301–305.

2. Borrelle, S. B., Ringma, J., Law, K. L., Monnahan, C. C., Lebreton, L., McGivern, A., Murphy, E., Jambeck, J., Leonard, G. H., Hilleary, M. A., Eriksen, M., Possingham, H. P., De Frond, H., Gerber, L. R., Polidoro, B., Tahir, A., Bernard, M., Mallos, N., Barnes, M., & Rochman, C. M. (2020). Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. Science, 369(6510), 1515–1518.

3. Valavanidis, Athanasios & Vlachogianni, Thomais. (2012). Marine Litter: Man-made Solid Waste Pollution in the Mediterranean Sea and Coastline. Abundance, Composition and Source Identification. WEB-SITE:www.chem-tox-ecotox.org. Science Advances on Environmental Chemistry, Toxicology and Ecotoxicology Issues .

4. Schuyler, Q. A., Wilcox, C., Townsend, K., Hardesty, B., & Marshall, N. (2014). Mistaken identity? Visual similarities of marine debris to natural prey items of sea turtles. BMC Ecology, 14(1), 14.

5. Zolotova, N., Kosyreva, A., Dzhalilova, D., Fokichev, N., & Makarova, O. (2022). Harmful effects of the microplastic pollution on animal health: a literature review. PeerJ, 10, e13503.

6. Nakayama, A., Yamano, N., & Kawasaki, N. (2019). Biodegradation in seawater of aliphatic polyesters. Polymer Degradation and Stability, 166, 290–299.

7. Niccolai E, Colzi I, Amedei A. Adverse Effects of Micro- and Nanoplastics on Humans and the Environment. Int J Mol Sci. 2023 Oct 31;24(21):15822.

8. Barnes, D. K. A., Galgani, F., Thompson, R. C., & Barlaz, M. (2009). Accumulation and fragmentation of plastic debris in global environments. Philosophical Transactions - Royal Society. Biological Sciences, 364(1526), 1985–1998.

9. Goldstein, M. C. (2012). Abundance and ecological implications of microplastic debris in the North Pacific Subtropical Gyre.

10. Law, K. L., & Thompson, R. C. (2014). Microplastics in the seas. Science, 345(6193), 144–145.

11. Li, Y., Sun, Y., Li, J., Tang, R., Miu, Y., & Ma, X. (2021). Research on the Influence of Microplastics on Marine Life. IOP Conference Series. Earth and Environmental Science, 631(1), 012006.

12. Jang, Y. C., Lee, J., Hong, S., Choi, H. W., Shim, W. J., & Hong, S. Y. (2015). Estimating the Global Inflow and Stock of Plastic Marine Debris Using Material Flow Analysis: a Preliminary Approach. Han-guk Haeyang Hwan-gyeongeneoji Hakoeji, 18(4), 263–273.

13. Wright, Pam (6 June 2017). "UN Ocean Conference: Plastics Dumped In Oceans Could Outweigh Fish by 2050, Secretary-General Says". The Weather Channel. Retrieved 5 May 2018.

14. Kumari, S., Agarwal, S., & Khan, S. (2022). Micro/nano glass pollution as an emerging pollutant in near future. Journal of Hazardous Materials Advances, 6, 100063.

15. https://businessday.ng/news/article/1382-shipping-containers-are-lost-at-sea-each-year-report/#:~:text=The%20World%20Shipping%20Council%20(WSC,This%20was%20up%20until 202019.

16. Title : Effects of a lost shipping container in the deep seaPersonal Author(s) : McDermott, Sydney;DeVogelaere, Andrew;Barry, Jim;Kahn, Amanda S.;Corporate Authors(s) : United States. National Ocean Service

17. Broadhurst, M. K., Suuronen, P., & Hulme, A. (2006). Estimating collateral mortality from towed fishing gear. Fish and Fisheries, 7(3), 180–218.

18. Gilardi, K. V., Carlson-Bremer, D., June, J. A., Antonelis, K., Broadhurst, G., & Cowan, T. (2010). Marine species mortality in derelict fishing nets in Puget Sound, WA and the cost/benefits of derelict net removal. Marine Pollution Bulletin, 60(3), 376–382.

19. Richardson, K., Hardesty, B. D., Vince, J., & Wilcox, C. (2022). Global estimates of fishing gear lost to the ocean each year. Science Advances, 8(41). https://doi.org/10.1126/sciadv.abq0135

20. Thushari, G., & Senevirathna, J. (2020). Plastic pollution in the marine environment. Heliyon, 6(8), e04709.

21. Thushari, G., & Senevirathna, J. (2020b). Plastic pollution in the marine environment. Heliyon, 6(8), e04709.

22. Willis, K., Hardesty, B. D., Kriwoken, L., & Wilcox, C. (2017). Differentiating littering, urban runoff and marine transport as sources of marine debris in coastal and estuarine environments. Scientific Reports, 7.

23. Thushari, G., & Senevirathna, J. (2020c). Plastic pollution in the marine environment. Heliyon, 6(8), e04709.

24. Moore, C. J. (2008). Synthetic polymers in the marine environment: A rapidly increasing, long-term threat. Environmental Research, 108(2), 131–139.

25. Gross, M. G. (1978). Effects of Waste Disposal Operations in Estuaries and the Coastal Ocean. Annual Review of Earth and Planetary Sciences, 6(1), 127–143.

26. Wan, S., Yang, X., Chen, X., Qu, Z., An, C., Zhang, B., . . . Bi, H. (2022). Emerging marine pollution from container ship accidents: Risk characteristics, response strategies, and regulation advancements. Journal of Cleaner Production, 376, 134266.

27. Moore, C., Moore, S., Leecaster, M., & Weisberg, S. (2001). A Comparison of Plastic and Plankton in the North Pacific Central Gyre. Marine Pollution Bulletin, 42(12), 1297–1300.

28. Lebreton, L., Slat, B., Ferrari, F., Sainte-Rose, B., Aitken, J., Marthouse, R., Hajbane, S., Cunsolo, S., Schwarz, A., Levivier, A., Noble, K., Debeljak, P., Maral, H., Schoeneich-Argent, R., Brambini, R., & Reisser, J. (2018). Evidence that the Great Pacific Garbage Patch is rapidly accumulating plastic. Scientific Reports, 8(1).

29. Frias, J., & Nash, R. (2019). Microplastics: Finding a consensus on the definition. Marine Pollution Bulletin, 138, 145–147.

30. Kühn, S., Rebolledo, E. B., van Franeker, J. A., Bergmann, M., Gutow, L., & Klages, M. (2015). Marine anthropogenic litter. Bergmann, M. Springer International Publishing, Marine anthropogenic litter, 75-116.

31. Van Franeker, J. A., Blaize, C., Danielsen, J., Fairclough, K., Gollan, J., Guse, N., ... & Turner, D. M. (2011). Monitoring plastic ingestion by the northern fulmar Fulmarus glacialis in the North Sea. Environmental pollution, 159(10), 2609-2615.

32. Nama, S., Shanmughan, A., Nayak, B. B., Bhushan, S., & Ramteke, K. (2023). Impacts of marine debris on coral reef ecosystem: A review for conservation and ecological monitoring of the coral reef ecosystem. Marine Pollution Bulletin, 189, 114755.

33. Koelmans, A. A., Besseling, E., & Foekema, E. M. (2014). Leaching of plastic additives to marine organisms. Environmental pollution, 187, 49-54.

34. McIlgorm, A., Raubenheimer, K., McIlgorm, D. E., & Nichols, R. (2022). The cost of marine litter damage to the global marine economy: Insights from the Asia-Pacific into prevention and the cost of inaction. Marine Pollution Bulletin, 174, 113167.

35. Goddijn-Murphy, L., Woolf, D. K., Pereira, R., Marandino, C. A., Callaghan, A. H., & Piskozub, J. (2023). The links between marine plastic litter and the air-sea flux of greenhouse gases. Frontiers in Marine Science, 10, 1180761.

36. Spengler, A., & Costa, M. F. (2008). Methods applied in studies of benthic marine debris. Marine Pollution Bulletin, 56(2), 226-230.

37. Watanabe, J. I., Shao, Y., & Miura, N. (2019). Underwater and airborne monitoring of marine ecosystems and debris. Journal of Applied Remote Sensing, 13(4), 044509.

38. Singh, D., & Valdenegro-Toro, M. (2021). The marine debris dataset for forward-looking sonar semantic segmentation. In Proceedings of the ieee/cvf international conference on computer vision (pp. 3741-3749).

39. LeCun, Y., Bengio, Y.., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.

40. M. Fulton, J. Hong, M. J. Islam and J. Sattar, "Robotic Detection of Marine Litter Using Deep Visual Detection Models," 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 2019, pp. 5752-5758.

41. Corrigan BC, Tay ZY, Konovessis D. Real-Time Instance Segmentation for Detection of Underwater Litter as a Plastic Source. Journal of Marine Science and Engineering. 2023; 11(8):1532. https://doi.org/10.3390/jmse11081532

42. Aleem, A., Tehsin, S., Kausar, S., & Jameel, A. (2022). Target Classification of Marine Debris Using Deep Learning. Intelligent Automation & Soft Computing, 32(1).

43. Bansal, M. A., Sharma, D. R., & Kathuria, D. M. (2022). A systematic review on data scarcity problem in deep learning: solution and applications. ACM Computing Surveys (CSUR), 54(10s), 1-29.

44. Katsanevakis, S. (2008). Marine debris, a growing problem: Sources, distribution, composition, and impacts. Marine Pollution: New Research. Nova Science Publishers, New York, 53-100.

45. Ahmad, I., Aslam, S., & Hussain, U. (2023). Assessment of plastic pollution in coastal areas of Karachi: Case study of West Warf, Kemari Jetty, and Manora. Marine Pollution Bulletin, 195,115501.

46. Watanabe, J. I., Shao, Y., & Miura, N. (2019). Underwater and airborne monitoring of marine ecosystems and debris. Journal of Applied Remote Sensing, 13(04),1.

47. T. Chrissley, M. Yang, C. Maloy and A. Mason, "Design of a Marine Debris Removal System," 2017 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 2017, pp. 10-15.

48. Yan, P., Abdulkadir, A., Luley, P. P., Rosenthal, M., Schatte, G. A., Grewe, B. F., & Stadelmann, T. (2024). A Comprehensive Survey of Deep Transfer Learning for Anomaly Detection in Industrial Time Series: Methods, Applications, and Directions. IEEE Access, 1.

49. 50.Tian, M., Li, X., Kong, S., Wu, L., & Yu, J. (2022). A modified YOLOv4 detection method for a vision-based underwater garbage cleaning robot. Frontiers of Information Technology & Electronic Engineering/Frontiers of Informaion Technology & Electronic Engineering, 23(8), 1217–1228.

50. Fulton, M., Hong, J., Islam, M. J., & Sattar, J. (2019b). Robotic Detection of Marine Litter Using Deep Visual Detection Models.

51. Hong, J., Fulton, M., & Sattar, J. (2020). A Generative Approach Towards Improved Robotic Detection of Marine Litter.

52. Xue, B., Huang, B., Wei, W., Chen, G., Li, H., Zhao, N., & Zhang, H. (2021). An Efficient Deep-Sea Debris Detection Method Using Deep Neural Networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 12348–12360.

53. Politikos, D. V., Fakiris, E., Davvetas, A., Klampanos, I. A., & Papatheodorou, G. (2021b). Automatic detection of seafloor marine litter using towed camera images and deep learning. Marine Pollution Bulletin, 164, 111974.

54. Jalil, B., Maggiani, L., & Valcarenghi, L. (2023b). Comparative analysis of machine learning algorithms for the classification of underwater marine debris.

55. Marin, I., Mladenović, S., Gotovac, S., & Zaharija, G. (2021). Deep-Feature-Based Approach to Marine Debris Classification. Applied Sciences, 11(12), 5644.

56. Music, J., Kruzic, S., Stancic, I., & Alexandrou, F. (2020). Detecting Underwater Sea Litter Using Deep Neural Networks: An Initial Study. 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech).

57. Hipolito, J. C., Alon, A. S., Amorado, R. V., Fernando, M. G. Z., & De Chavez, P. I. C. (2021). Detection of Underwater Marine Plastic Debris Using an Augmented Low Sample Size Dataset for Machine Vision System: A Deep Transfer Learning Approach.

58. Hu, Z., & Xu, C. (2022b). Detection of Underwater Plastic Waste Based on Improved YOLOv5n.

59. Ghadekar, P., Dhadiwal, A., Shinde, A., Sharma, D., Khare, S., & Agrawal, R. (2023). Efficient classification, detection and analysis of submerged marine debris. AIP Conference Proceedings.

60. Ma, D., Wei, J., Li, Y., Zhao, F., Chen, X., Hu, Y., Yu, S., He, T., Jin, R., Li, Z., & Liu, M. (2023). MLDet: Towards efficient and accurate deep learning method for Marine Litter Detection. Ocean & Coastal Management, 243, 106765.

61. M, N. B., DhanyaS, N., R, N. G., & KirthikaKG, N. (2022b). Marine Plastic Detection Using Deep Learning. In Advances in parallel computing.

62. M. Tian, X. Li, S. Kong, L. wu and J. Yu, "Pruning-Based YOLOv4 Algorithm for Underwater Gabage Detection," 2021 40th Chinese Control Conference (CCC), Shanghai, China, 2021, pp. 4008-4013.

63. Corrigan, B. C., Tay, Z. Y., & Konovessis, D. (2023). Real-Time Instance Segmentation for Detection of Underwater Litter as a Plastic Source. Journal of Marine Science and Engineering, 11(8), 1532.

64. Valdenegro-Toro, M. (2016b). Submerged marine debris detection with autonomous underwater vehicles.

65. Li, X., Tian, M., Kong, S., Wu, L., & Yu, J. (2020). A modified YOLOv3 detection method for vision-based water surface garbage capture robot. International Journal of Advanced Robotic Systems, 17(3), 172988142093271.

66. Tata, G., Royer, S. J., Poirion, O., & Lowe, J. (2021). A robotic approach towards quantifying epipelagic bound plastic using deep visual models. arXiv preprint arXiv:2105.01882.

67. Fulton, M., Hong, J., Islam, M. J., & Sattar, J. (2019, May). Robotic detection of marine litter using deep visual detection models. In 2019 international conference on robotics and automation (ICRA) (pp. 5752-5758). IEEE.

68. M. Fulton, J. Hong, M. J. Islam and J. Sattar, "Robotic Detection of Marine Litter Using Deep Visual Detection Models," 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 2019, pp. 5752-5758.

69. Xue, B., Huang, B., Wei, W., Chen, G., Li, H., Zhao, N., & Zhang, H. (2021). An efficient deep-sea debris detection method using deep neural networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 12348-12360.

70. Politikos, D. V., Fakiris, E., Davvetas, A., Klampanos, I. A., & Papatheodorou, G. (2021c). Automatic detection of seafloor marine litter using towed camera images and deep learning. Marine Pollution Bulletin, 164, 111974.

71. Jalil, B., Maggiani, L., & Valcarenghi, L. (2023, October). Comparative analysis of machine learning algorithms for the classification of underwater marine debris. In 2023 IEEE.

72. Marin, I., Mladenović, S., Gotovac, S., & Zaharija, G. (2021b). Deep-Feature-Based Approach to Marine Debris Classification. Applied Sciences, 11(12), 5644.

73. Hipolito, J. C., Alon, A. S., Amorado, R. V., Fernando, M. G. Z., & De Chavez, P. I. C. (2021, November). Detection of Underwater Marine Plastic Debris Using an Augmented Low Sample Size Dataset for Machine Vision System: A Deep Transfer Learning Approach. In 2021 IEEE 19th Student Conference on Research and Development (SCOReD) (pp. 82-86). IEEE.

74. Hu, Z., & Xu, C. (2022c). Detection of Underwater Plastic Waste Based on Improved YOLOv5n.

75. Ghadekar, P., Dhadiwal, A., Shinde, A., Sharma, D., Khare, S., & Agrawal, R. (2023b). Efficient classification, detection and analysis of submerged marine debris. AIP Conference Proceedings.

76. Ma, D., Wei, J., Li, Y., Zhao, F., Chen, X., Hu, Y., Yu, S., He, T., Jin, R., Li, Z., & Liu, M. (2023b). MLDet: Towards efficient and accurate deep learning method for Marine Litter Detection. Ocean & Coastal Management, 243, 106765.

77. Hemanth, D. J. (2022). Marine Plastic Detection Using Deep Learning. Advances in Parallel Computing Algorithms, Tools and Paradigms, 41, 406.

78. Tian, M., Li, X., Kong, S., Wu, L., & Yu, J. (2022b). A modified YOLOv4 detection method for a vision-based underwater garbage cleaning robot. Frontiers of Information Technology & Electronic Engineering/Frontiers of Informaion Technology & Electronic Engineering, 23(8), 1217–1228.

79. Corrigan, B. C., Tay, Z. Y., & Konovessis, D. (2023b). Real-Time Instance Segmentation for Detection of Underwater Litter as a Plastic Source. Journal of Marine Science and Engineering, 11(8), 1532.

80. http://www.godac.jamstec.go.jp/catalog/dsdebris/e/index.html

81. J. Music, S. Kružić, I. Stančić and F. Alexandrou, "Detecting Underwater Sea Litter Using Deep Neural Networks: An Initial Study," 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 2020, pp. 1-6.

82. Sánchez-Ferrer, A., Valero-Mas, J. J., Gallego, A. J., & Calvo-Zaragoza, J. (2023). An experimental study on marine debris location and recognition using object detection. Pattern Recognition Letters, 168, 154–161.