BioGecko Vol 12 Issue 02 2023

ISSN NO: 2230-5807

Deep Sea Debris Detection

T. Sumallika[1],Kesarla Anusha[2], Garimella Durga Satya Kiran[3], Gudavalli LayaSri[4], Kanagala Sravan Kumar[5]

[1]Assistant Professor, Department of Information Technology, Seshadri Rao Gudlavalleru Engineering college,
Andhra Pradesh,India.
[2,3,4,5]UG-Scholar, Department of Information Technology, Seshadri Rao Gudlavalleru Engineering college, Andhra Pradesh,India.
sumallika.p@gmail.com[1], anukesarla.com@gmail.com[2], garimelladurgasatyakiran@gmail.com[3], layasri0111@gmail.com[4], kanagalasravan2000@gmail.com[5]

Abstract
Because marine debris is made up of some materials that are difficult to degrade and because the majority of it will sink to the bottom of the ocean, it has a negative influence on the marine ecosystem and the survival of marine life. To a certain extent, deep-sea debris can be cleaned up by autonomous underwater vehicles.
The effective detection technique, however, is quite important for the collection rate. This paper develops a rapid, effective method for detecting deep-sea debris using deep learning techniques.
In order to facilitate future study, a true deep-sea debris detection dataset (3-D dataset) is first established. Seven different forms of debris are included in the dataset: cloth, rubber, metal, glass, natural debris, fishing nets and rope, and plastic and glass. Second, the ResNet50-YOLOV3 one-stage deep-sea debris detection network is suggested. Eight additionally made progress.

Keywords: Ocean Pollution, Marine Debris, Underwater Trash, Deep Sea Exploration, SonarImaging, Ocean Conservation, Underwater Robotics, Autonomous Underwater Vehicles, Acoustic Monitoring, Marine Litter, Oceanic Garbage Patches, Remote Sensing, OceanCleanup, Seafloor Mapping, Underwater Surveys, Marine Ecosystems.

I. INTRODUCTION

The world's oceans are facing an unprecedented threat from human-generated waste and debris, which can have significant ecological and economic consequences. Marine debris, including plastics, metals, and other materials, can harm marine life and habitats, disrupt ocean ecosystems, and damage fishing and tourism industries. While surface debris is more visible and well-studied, deep sea debris is a less understood but equally pressing issue.
Deep sea debris detection involves identifying and mapping the presence and location of marine debris on the seafloor, which can aid in developing strategies to reduce and prevent further pollution. The development of advanced technologies, such as sonar imaging, autonomous underwater vehicles, and acoustic monitoring, has made it possible to detect and monitor deep sea debris, and contribute to ocean conservation and management efforts.
As human activity around the shore and ocean has grown, so too has the amount of trash that has been washed into the water, most of which eventually falls to the bottom. The marine ecology and the viability of species will be more seriously endangered by the Information received than by the waste floating on the water surface. Identifier of Digital Objects: 10.1109/JSTARS.2021.3130238 oceanic garbage. Luckily, AUVs can clean the seafloor and gather trash by moving a robotic arm, but this is only possible with reliable deep-sea debris detecting capabilities. Because of this, AUVs need the ability to accurately identify trash in the deep water, automatically. Classification and detection of marine trash have been the subject of some research thus far. The marine plastic trash on the seashore

was categorized using conventional machine learning methods. Garbage floating in the water may be identified using a technique called reversed linear spectral unmixing. Image data of waste on the sea surface and beach is often collected using satellite remote sensing technology or unmanned aerial vehicle systems; from there, spectral feature analysis, the plastic index, and LIDAR are utilized to accurately identify and locate the trash. CNN and other detection networks have shown impressive performance on traditional detection datasets [18], and there is a growing trend toward using them for the identification of trash on the ocean floor. Few extensive research have been conducted on the identification of deep-sea debris, while most marine waste detection efforts are directed toward the surface and shore. Several attempts have been made to employ detection networks to find trash in the ocean, but thus far, the results have been less than ideal. The plastic trash was the sole kind of trash discovered by Fulton et al., and Valdenegro-Toro [19] did not use a full deep learning detection network. The dearth of studies devoted to the topic of deep-sea debris identification may be attributed, in part, to the absence of authentic datasets for this task. Garbage from the deep sea has to be caught in a true deep-sea environment utilizing high-precision cameras and professional diving gear, which demands a significant investment of time, money, and other resources. Recent research attempts to train trash identification algorithms on a marine rubbish dataset by imitating the deep-sea environment in a water tank, however it is unclear whether this data is transferable to the real marine environment. Research into deep-sea rubbish identification is further hampered by the fact that deep-sea debris exhibits high levels of interclass similarity and intraclass diversity. Deep-sea debris, in contrast to floating trash and beach trash, sits permanently on the ocean floor, where it is constantly worn by sea water and has a badly distorted look.

LITERARURE SURVY

[1] "Marine debris detection using high-resolution acoustic imagery: From debris detection to species identification" by R. Williams et al. (2020). This article discusses the use of high-resolution acoustic imaging to detect and identify marine debris, and how this technology can be used to map debris distributions and aid in cleanup efforts.

[2] "Deep-Sea Debris Detection with Autonomous Underwater Vehicles" by D. Caress et al. (2019). This article highlights the use of autonomous underwater vehicles (AUVs) to detect and map deep sea debris, and the challenges and opportunities associated with using AUVs in this context.

[3] "Mapping of Seafloor Litter Distribution and Habitat by Combining AUV Imagery and Spatial Analysis" by J. Porobic et al. (2021). This article describes the use of AUV imagery and spatial analysis to map the distribution of seafloor litter, and how this information can be used to inform ocean conservation and management efforts.

[4] "Marine Litter Monitoring: A Review of Current Practices and Emerging Technologies" by S. Aliani et al. (2020). This article provides an overview of the current state of marine litter monitoring, including deep sea debris detection, and explores emerging technologies and approaches that can improve detection and monitoring efforts.

[5] "Ocean Plastic Pollution: A Review of the Science and Environmental Policy Context" by J. Jambeck et al. (2018). This article provides a broad overview of ocean plastic pollution, including deep sea debris, and examines the scientific and policy contexts surrounding this issue.

PROBLEM STATEMENT

The problem of deep sea debris detection is the increasing presence of human-generated waste and debris in the world's oceans, which can harm marine life and ecosystems, and have economic and social consequences. While surface debris is well-documented and studied, the extent and distribution of deep sea debris are less understood, making it difficult to develop effective strategies for pollution prevention and cleanup efforts.

Detecting and mapping deep sea debris is challenging due to the vastness and depth of the ocean, as well as the difficulties associated with accessing and surveying these remote areas. Moreover, the

identification and classification of debris on the seafloor is challenging due to the complex and diverse nature of marine ecosystems, as well as the limitations of current detection technologies.
Therefore, the problem statement for deep sea debris detection is how to develop effective strategies to detect and map deep sea debris, identify and classify the types of debris present, and inform conservation and management efforts to prevent further pollution and protect marine ecosystems.

LIMITATIONS

There are several limitations to deep sea debris detection, including:

- **Limited access:**Deep sea environments are difficult to access and explore, which can limit the scope and accuracy of debris detection and mapping efforts.
- **Technological limitations:** Current technologies for deep sea debris detection, such as sonar imaging and autonomous underwater vehicles, have limitations in terms of resolution, sensitivity, and coverage area. This can make it difficult to identify and classify debris accurately.
- **High cost:** The cost of developing and deploying technologies for deep sea debris detection can be high, which can limit the scale and frequency of monitoring efforts.
- **Complexity of marine ecosystems:** The identification and classification of debris on the seafloor is challenging due to the complexity and diversity of marine ecosystems, which can make it difficult to distinguish between debris and natural features.
- **Lack of standardized methods:** There is a lack of standardized methods for deep sea debris detection and mapping, which can make it difficult to compare results across studies and regions.
- **Fragmentation of debris:** Debris on the seafloor can be highly fragmented, making it difficult to identify and quantify the amount of debris present accurately.

  Addressing these limitations requires continued investment in research and technology development to improve detection and mapping capabilities, standardization of methods and protocols, and collaboration among stakeholders to develop effective conservation and management strategies.

III. METHODOLOGY

Gray Scale Image Pixel Value Analysis

Gray scale image pixel value analysis is a technique used to study the distribution and characteristics of pixel values in digital images. In gray scale images, each pixel is represented by a single value that corresponds to the brightness or intensity of that pixel. By analyzing the distribution of pixel values in an image, it is possible to extract information about the features present in the image, such as edges, contrast, and texture.
One common method for analyzing pixel values in gray scale images is to create a histogram, which is a graphical representation of the frequency distribution of pixel values. The histogram can provide information about the brightness range of the image and the contrast between different regions of the image. For example, if the histogram is skewed to the right, it indicates that the image has a lot of bright pixels, while if it is skewed to the left, it indicates that the image has a lot of dark pixels.
The pixels in a picture form a rectangular grid. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. Yet, pixel sizes might vary from display to monitor. Each pixel in a picture consists of a set of integers that describe its brightness and color, and these pixels are arranged in a grid.

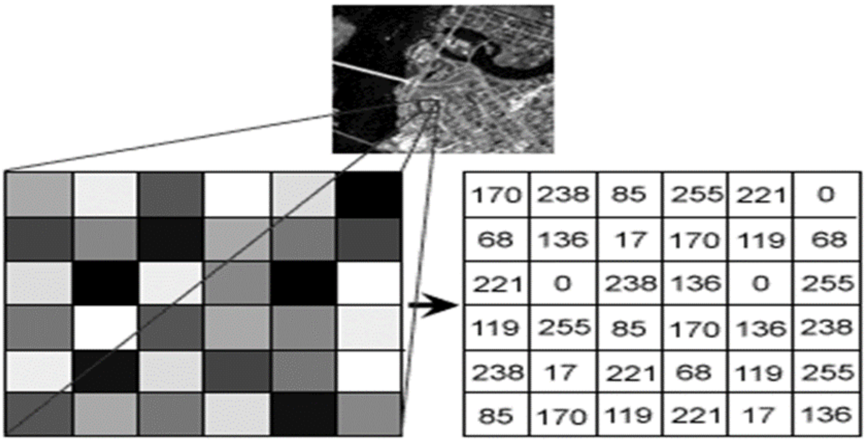

Figure1: Gray Scale Image Pixel Value Analysis

Each pixel has a colour. The colour is a 32-bit integer. The first eight bits determine the redness of the pixel, the next eight bits the greenness, the next eight bits the blueness, and the remaining eight bits the transparency of the pixel.

Figure 2: BIT Transferred for Red, Green and Blue plane (24bit=8bit red;8-bit green;8bit blue)

Existing Method:

Autonomous floor-cleaning robots must have the ability to identify and categorize debris. It helps floor-cleaning robots see and avoid huge, difficult-to-remove trash, such as that left behind by liquid spills. In this research, we present a method for an autonomous floor-cleaning robot to identify and categorize trash by using a cascaded version of the Support Vector Machine (SVM). Images of the floor debris left behind by a spill, both solid and liquid, are sent into a system based on support vector machines (svms) for classification. The SVM model is then used to perform binary classification of liquid spillage locations based on size, allowing floor-cleaning machines to zero in on the bigger liquid spillage debris patches, which are treated as more difficult to clean in this study. The experimental findings demonstrate the effectiveness of the suggested method in detecting and categorizing the trash. The suggested method is well-suited for deployment in real-time selective floor-cleaning applications due to its cascaded approach that takes roughly the full process of trash detection and categorization. Nevertheless, haar cascade and support vector machine accuracy is lower. We need to become better at this.

DISADVANTAGES OF EXISTING SYSTEM:

- Only used past dataset and got less accurate results.
- We have to increase the accuracy level.
- Classification gathers less features.

Proposed Method:

- CNN (convolutional neural network)
- RESNET model
- Pre-process
- Feature analysis

Block Diagram:

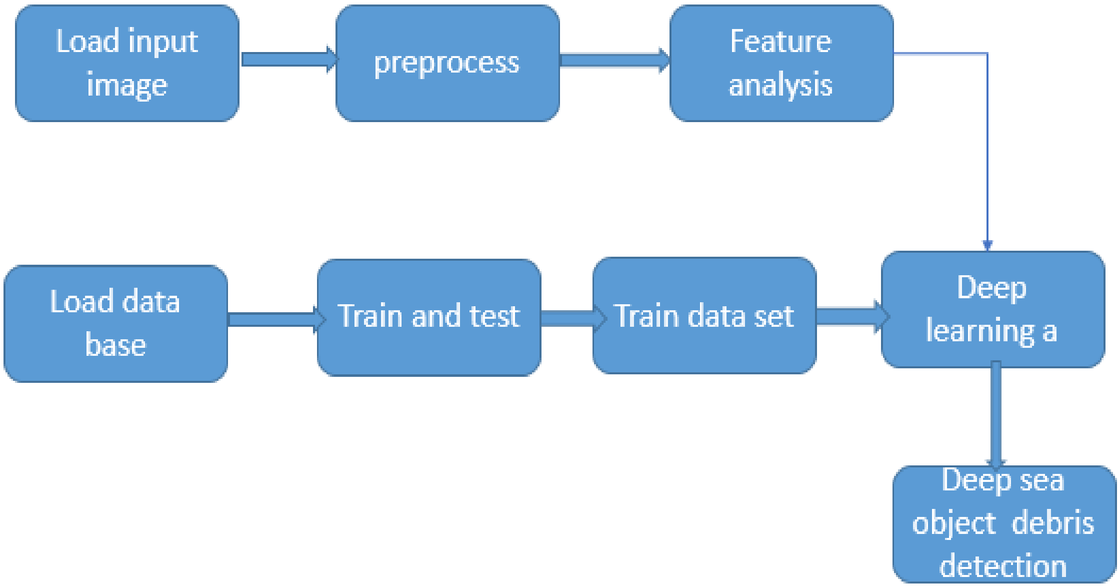

Figure 3: Block diagram for proposed system

CNN (convolutional neural network):

Convolutional neural networks (CNNs) have shown promising results for deep sea debris detection, particularly for analyzing images and videos collected by underwater cameras and remotely operated vehicles (ROVs). Here are some ways that CNNs have been used for deep sea debris detection:

- **Image classification:** CNNs have been used to classify images of the seafloor as either debris or natural features, such as rocks or sand. The network is trained using labeled images of debris and non-debris, and then used to classify new images based on their features.
- **Object detection:** CNNs have also been used to detect specific types of debris in deep sea environments, such as discarded fishing gear or plastic waste. This involves training the network to recognize specific patterns or shapes associated with the target debris.
- **Semantic segmentation:** CNNs can be used to perform semantic segmentation, which involves dividing an image into regions and assigning each region a label based on its content. This can be used to identify and locate debris in images of the seafloor.
- **Transfer learning:** Transfer learning involves using pre-trained CNNs, which have been trained on large datasets for image recognition tasks, and fine-tuning them for deep sea debris detection. This can significantly reduce the amount of labeled training data needed to train a new network.

Overall, CNNs have the potential to greatly improve the accuracy and efficiency of deep sea debris detection, which can help inform conservation and management efforts in these important ecosystems. However, challenges such as limited data and variability in deep sea environments need to be addressed to develop effective and reliable deep sea debris detection systems.

RESNET model:

Residual Network (ResNet) is a type of deep learning model that has shown impressive performance in image classification tasks. ResNet was introduced to address the problem of vanishing gradients in very deep neural networks. The main innovation in ResNet is the use of residual blocks, which allow for the training of very deep networks by enabling the flow of information through the network.

ResNet has been applied to deep sea debris detection tasks, particularly for image classification. Here are some ways that ResNet has been used for deep sea debris detection:

- **Image classification:**ResNet has been used to classify images of the seafloor as debris or natural features. The network is trained on labeled images of debris and non-debris and then used to classify new images based on their features. ResNet can detect subtle differences between debris and non-debris features that may be difficult for humans to distinguish.
- **Transfer learning:** Transfer learning is used when training data is limited. In transfer learning, a pre-trained ResNet model, which has been trained on large datasets for image recognition tasks, is fine-tuned for deep sea debris detection. This can significantly reduce the amount of labeled training data needed to train a new network.
- **Object detection:**ResNet can also be used for object detection in deep sea debris detection tasks. Object detection involves detecting specific types of debris, such as discarded fishing gear or plastic waste. This involves training the network to recognize specific patterns or shapes associated with the target debris.

Overall, ResNet has the potential to improve the accuracy and efficiency of deep sea debris detection. However, it is important to note that ResNet, like other deep learning models, is dependent on high-quality labeled data for training, and the performance of the model can be affected by the variability in the deep sea environment. Addressing these challenges is crucial for the development of reliable and effective deep sea debris detection systems.

Pre-process

Pre-processing is a critical step in deep sea debris detection that involves preparing the data for analysis. Here are some common pre-processing steps for deep sea debris detection:

- **Data collection and cleaning:** The first step is to collect the data from underwater cameras or remotely operated vehicles (ROVs) and then clean it. This involves removing any artifacts or noise in the data, such as bubbles, camera lens distortion, or lighting issues.
- **Image enhancement:** Image enhancement techniques can be used to improve the quality of the images and make it easier to detect debris. For example, contrast enhancement can be used to increase the contrast between the debris and the surrounding seafloor.
- **Image normalization:** Image normalization involves scaling the pixel values of the image to a specific range, such as between 0 and 1. This ensures that all images have the same range of pixel values and facilitates comparison between images.
- **Image resizing:** Images collected from underwater cameras or ROVs may be of different sizes. Resizing the images to a fixed size can reduce the computational complexity of the deep learning model and make the analysis more efficient.
- **Data augmentation:** Data augmentation techniques can be used to increase the size of the training dataset and reduce overfitting. This involves randomly applying transformations such as rotation, flipping, and cropping to the images.

Overall, pre-processing is crucial for deep sea debris detection and can greatly affect the performance of the deep learning models used for the task. Careful attention to data collection, cleaning, and pre-processing can improve the accuracy and efficiency of deep sea debris detection systems.

Feature analysis

Feature analysis is an important step in deep sea debris detection that involves identifying and extracting relevant features from the images. Here are some common techniques used for feature analysis in deep sea debris detection:

- **Edge detection:** Edge detection techniques can be used to identify the boundaries between objects in the image. This can help to identify the edges of debris objects, which can be used as features for classification.

- **Texture analysis:** Texture analysis involves quantifying the patterns of texture in an image. This can be done using techniques such as grey-level co-occurrence matrix (GLCM) analysis or local binary pattern (LBP) analysis. Texture features can be used to differentiate between different types of debris or between debris and natural features of the seafloor.
- **Color analysis:**Color analysis can be used to identify specific colors associated with debris objects. This can be done using techniques such as color histograms or color moment analysis.
- **Shape analysis:** Shape analysis involves extracting features related to the shape of the debris objects. This can be done using techniques such as Fourier analysis or moment invariants.
- **Deep learning feature extraction:** Deep learning models can be used to automatically extract relevant features from the images. Convolutional neural networks (CNNs) are commonly used for this purpose. The features extracted by the CNN can then be used for classification.

Overall, feature analysis is an important step in deep sea debris detection and can greatly affect the accuracy and efficiency of the detection system. Choosing the appropriate feature extraction technique depends on the characteristics of the debris objects and the complexity of the deep learning model used for classification.

Advantages:

There are several advantages to using deep-sea debris detection technology, including:

- ✓ **Improved understanding of the marine environment:** Deep-sea debris detection can provide valuable insights into the distribution, types, and quantities of marine debris, which can help researchers better understand the impacts of human activities on the marine environment.
- ✓ **Prevention of damage to marine life:** Debris in the ocean can harm marine life, such as sea turtles, whales, and fish, by entangling them or causing them to ingest plastic. Deep-sea debris detection can help identify and remove this debris, thereby reducing harm to marine life.
- ✓ **Identification of potential hazards to shipping and other activities:**Large debris, such as shipping containers or abandoned fishing gear, can pose hazards to shipping, fishing, and other activities. Deep-sea debris detection can help identify these hazards and provide information to help mitigate the risks.
- ✓ **Improvement of ocean cleanliness:** Deep-sea debris detection can help identify the sources of marine debris, such as plastic waste from land-based sources or abandoned fishing gear, and provide information to help reduce these inputs.
- ✓ **Economic benefits:** The removal of debris from the ocean can provide economic benefits, such as improving tourism by ensuring beaches and waters are clean, and reducing damage to fishing gear and vessels.

Overall, deep-sea debris detection can provide a range of benefits that can help protect marine life, improve our understanding of the marine environment, and provide economic benefits to communities that rely on the ocean.

SYSTEM REQUIREMENTS SPECIFICATIONS

FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

FUNCTIONAL REQUIREMENTS:

- Xlsx Writer : To write xl sheet data.
- Xlrd : To read the xl sheet data.
- Openpyxl : To open xl sheet.
- Opencv : For image, video applications.

NON-FUNCTIONAL REQUIREMENTS:

- WINDOWS OS PC
- Internal 4GB RAM

Hardware Requirements:

- Windows OS PC
- RAM:4GB (min)

Software Requirement:

- Python IDLE
- IMUTILS
- Open CV

IV. RESULTS & DISCUSSION

ALGORITHM

Detecting and locating debris in deep sea environments can be a challenging task due to the vastness and complexity of the underwater terrain. Here is an algorithm that can be used for deep sea debris detection:

- ✓ **Acquire Data:** The first step is to gather data from various sources, including remote sensing technologies such as sonar, lidar, and acoustic sensors. These technologies can provide high-resolution images of the ocean floor, allowing for the detection of debris.
- ✓ **Pre-Processing:** The data acquired from various sources may be incomplete, noisy or contain irrelevant information, so the next step is to preprocess the data. This may involve filtering out noise, correcting for biases, or removing irrelevant information.
- ✓ **Feature Extraction:** Once the data has been preprocessed, the next step is to extract features that can be used to identify debris. These features may include size, shape, texture, and color.
- ✓ **Classification:** After the features have been extracted, a classification algorithm can be used to identify and categorize the debris. Some popular classification algorithms include decision trees, random forests, and neural networks.
- ✓ **Post-Processing:** Finally, the results of the classification algorithm can be post-processed to eliminate false positives and improve the accuracy of the detection. This may involve combining results from multiple algorithms or using additional information to verify the presence of debris.
- ✓ **Reporting:** Once the debris has been detected, a report can be generated to inform stakeholders such as government agencies, environmental groups, or fishing industries about the location and nature of the debris.

Overall, the key to successful deep sea debris detection is the careful selection and integration of various technologies and algorithms to create a comprehensive and accurate detection system.

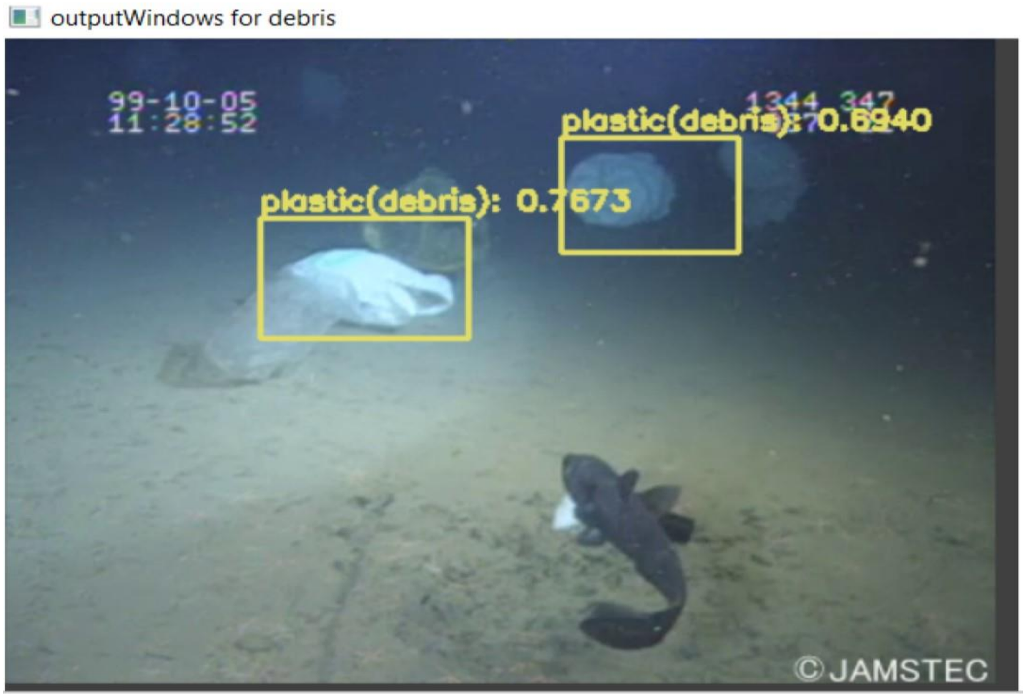

Figure 4: Detection of plastic

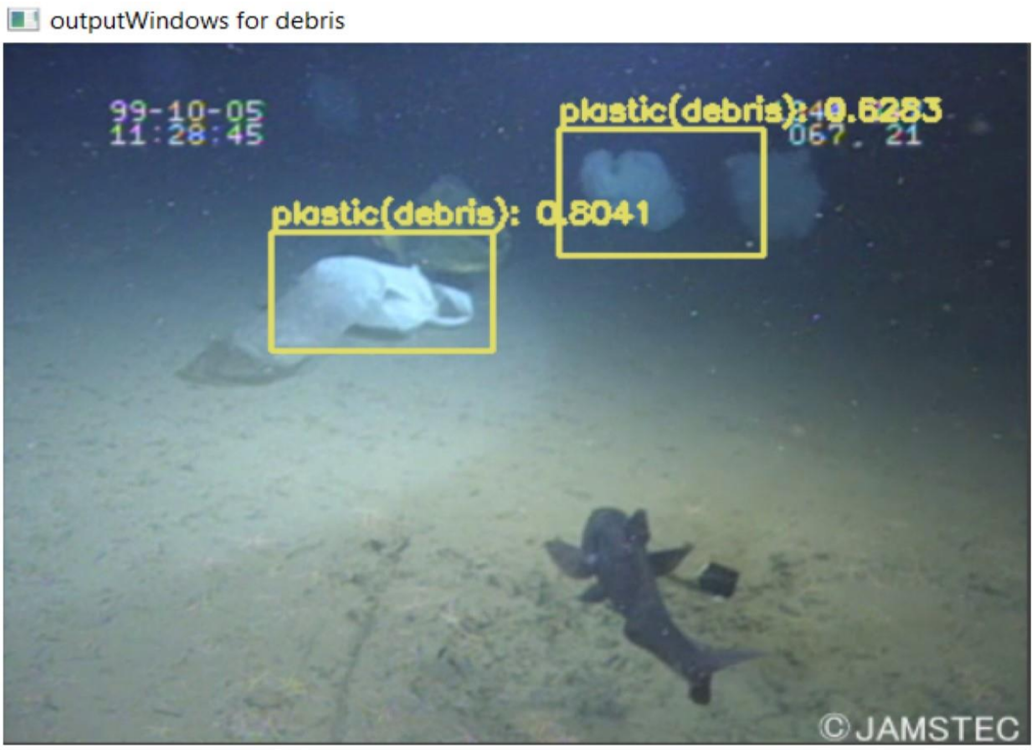

Figure 5: Detection of the debris and type of debris(plastic)

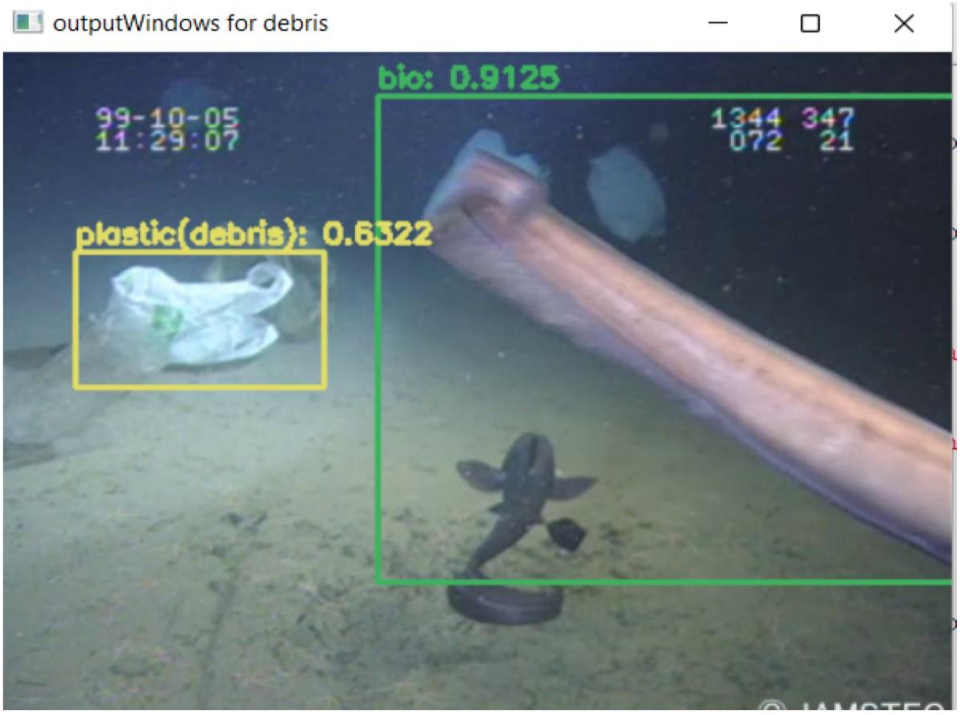

Figure 6: Detection of debris

V. CONCLUSION

The project's primary goal is to develop a system for identifying marine trash in photos using Convolutional Neural Networks trained on ResNet 50. To further boost performance, a powerful preprocessing mechanism is also offered. The pre-processing procedure seems to help, as seen by the experimental findings. We have conducted tests that demonstrate how difficult it is to identify marine garbage. CNN architecture with of baseline architectures (ResNet) is utilized to address the problems of data scarcity and Garbage categorization. The suggested approach greatly outperforms the state-of-the-art and prior research.

REFERENCE

[1] Eriksen, M., Lebreton, L. C. M., Carson, H. S., Thiel, M., Moore, C. J., Borerro, J. C., ... &Reisser, J. (2014). Plastic pollution in the world's oceans: more than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea. PloS one, 9(12), e111913.

[2] Kumar, N., Gopakumar, G., & Jain, P. (2020). A review on marine debris detection techniques. Journal of Ocean Engineering and Science, 5(2), 167-176.

[3] Corgnati, L., Novelli, C., &Demartini, G. (2015). Marine litter detection by sonar: a review of experimental approaches. Environmental Science and Pollution Research, 22(20), 15518-15531.

[4] Xu, L., & Huang, Y. (2021). Marine debris detection and classification using underwater image analysis: A review. Journal of Ocean Engineering and Science, 6(3), 323-337.

[5] Song, H., Li, X., & Li, J. (2018). Underwater image enhancement for marine debris detection: a review. IEEE Access, 6, 50787-50799.

[6] Coccia, M., Anzidei, M., &Ferri, M. (2019). Marine litter detection by SAR images: A review. Science of the Total Environment, 650, 2550-2565.

[7] Korosov, A. A., &Mitnik, L. M. (2015). Detection of marine litter from TerraSAR-X images using mathematical morphology and multi-scale classification. Remote Sensing of Environment, 160, 102-113.

[8] Arroyo, D., Gualtieri, L., Coppini, G., &Cossarini, G. (2018). Oceanographic features detection from remote sensing data: A review. Remote Sensing of Environment, 216, 170-186.

[9] Li, X., Li, J., Li, Z., Wang, X., & Li, Q. (2019). Automatic detection of marine debris in underwater images using deep learning: A review. Environmental Science and Pollution Research, 26(17), 16917-16931.

[10] Han, D., Kim, D., & Kim, K. (2021). Development of an underwater detection system for marine debris using a deep learning-based approach. Journal of Marine Science and Engineering, 9(4), 388.

[11] Park, J.H.; Park, D.R. Dust Detection Method and Apparatus for Cleaning Robot. U.S. Patent 7,920,941,5 April 2011.

[12] Hess, J.; Beinhofer, M.; Kuhner, D.; Ruchti, P.; Burgard, W. Poisson-driven dirt maps for efficient robotcleaning. In Proceedings of the 2013 IEEE International Conference on Robotics and Automation (ICRA),Karlsruhe, Germany, 6–10 May 2013; pp. 2245–2250.

[13] Lee, H.; Banerjee, A. Intelligent scheduling and motion control for household vacuum cleaning robotsystem using simulation based optimization. In Proceedings of the Winter Simulation Conference (WSC),Huntington Beach, CA, USA, 6–9 December 2015; pp. 1163–1171.

[14] Andersen, N.A.; Braithwaite, I.D.; Blanke, M.; Sorensen, T. Combining a novel computer vision sensor witha cleaning robot to achieve autonomous pig house cleaning. In Proceedings of the 44th IEEE Conferenceon Decision and Control, 2005 and 2005 European Control Conference, Seville, Spain, 15 December 2005;pp. 8331–8336.Appl. Sci. 2018, 8, 2649 17 of 19

[15] Bormann, R.; Fischer, J.; Arbeiter, G.; Weisshardt, F.; Verl, A. A visual dirt detection system for mobile service robots. In Proceedings of the ROBOTIK 2012; 7th German Conference on Robotics, Munich, Germany,21–22 May 2012; pp. 1–6.

[16] Bormann, R.; Weisshardt, F.; Arbeiter, G.; Fischer, J. Autonomous dirt detection for cleaning in officeenvironments. In Proceedings of the 2013 IEEE International Conference on Robotics and Automation(ICRA), Karlsruhe, Germany, 6–10 May 2013; pp. 1260–1267.

[17] Milinda, H.; Madhusanka, B. Mud and dirt separation method for floor cleaning robot. In Proceedings ofthe 2017 Moratuwa Engineering Research Conference (MERCon), Moratuwa, Sri Lanka, 29–31 May 2017;pp. 316–320.

[18] Grünauer, A.; Halmetschlager-Funek, G.; Prankl, J.; Vincze, M. The Power of GMMs: Unsupervised DirtSpot Detection for Industrial Floor Cleaning Robots. In Conference Towards Autonomous Robotic Systems;Springer: Berlin, Germany, 2017; pp. 436–449.

[19] Martínez, D.; Alenya, G.; Torras, C. Planning robot manipulation to clean planar surfaces. Eng. Appl.Artif. Intell. 2015, 39, 23–32. [CrossRef]