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An AI-Powered System for Real-Time Underwater Plastic Detection and Classification Using YOLOv7 and VGG16

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Abstract

Plastic pollution in marine environments poses a severe threat to aquatic ecosystems and global biodiversity. The traditional methods used to monitor the wastes in the sea are time consuming and in virtually every situation, not real time responsive. In order to achieve effective and efficient plastic underwater detection and classification, the current paper proposes a hybrid architecture that incorporates YOLOv7, a newly emerging object detector architecture, and VGG16, a deep convolutional neural network. The system is able to detect the plastic waste and classify it into different categories, such as bottles, bags, nets, and wrappers. An SMTP notification system is proposed to simplify the detection, while an email notification with annotated detection result is recommended to be sent at each plastic detection. It could be to train YOLOv7 on large amounts of underwater images to predict where they are in general and then use VGG16 to predict exactly where they are in cropped regions. The tests show that the system is highly accurate and performant under extreme conditions in the under-sea environment, including turbidity or low visibility. The automatic alerter also provides early alerting and immediate response and remediation. Overall, the book is a brilliant, measured, terrestrial effort to solve the problem of marine waste disposal and contributes to the body of literature on environmental protection and building a sustainable ecosystem.

Keywords: Underwater plastic detection, YOLOv7, VGG16, Deep learning, Plastic classification, Marine pollution monitoring, Real-time detection, SMTP alert system, Environmental conservation, Computer vision.

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1. Introduction

One of the most significant environmental problems of the twenty-first century is plastic pollution. Every year, many millions of tons of plastic debris are dumped into the oceans, endangering human health, food security, and marine biodiversity. In addition to harming aquatic life within ingestion and entanglement, other wastes such as beverage bottles, plastic bags, and fishing nets also disrupt their habitat and lower water quality. Despite the fact that the problem of plastic has become widely recognized, there are still very few practical methods for managing and observing plastic underwater. Conventional techniques, which are costly, time-consuming, and unable to provide real-time data at large scales, include direct observation and distantly operated vehicle systems.

Finding answers and creating AIs that can recognize and label underwater debris have been made possible by recent developments in computing vision and deep learning. When compared to convolution networks like VGG16 for small- scale image classification, the detection model YOLO has demonstrated high precision and effectiveness in real-time.

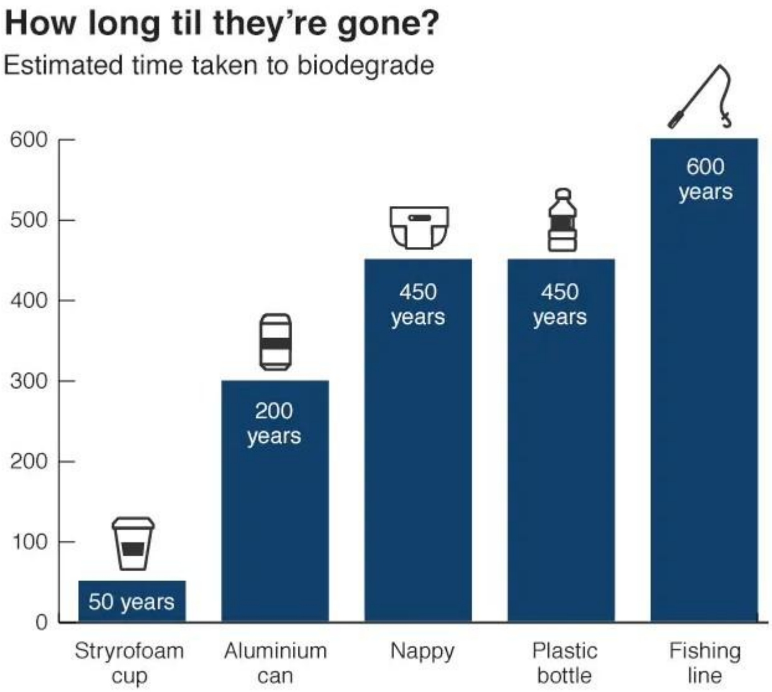

Fig. 1. Time Taken for Biodegrade

1.1. Objectives

1) To develop an intelligent system for real-time underwater plastic detection using YOLOv7.
2) To classify detected plastics into specific categories such as bottles, bags, nets, and wrappers using VGG16.
3) To integrate an SMTP-based email alert mechanism for immediate notification of detection results.
4) To ensure robust performance under challenging underwater conditions such as low visibility, turbidity, and noise.
5) To provide a scalable solution that can be extended to large-scale marine monitoring and conservation efforts.

The paper's objective is to develop a DL-powered model that can recognize and classify plastic debris in underwater settings. The YOLOv7 will be used to detect the waste, the VGG16 will identify the type of recyclable class, and SMTP alerting will be used to supply current notifications for this waste. preciseness, scalability, and the inclusion of ports, coastal nature reserves, and coastal areas are the key objectives. It has to do with big plastic waste, like bottles, bags, nets, and wrappers.Given the increasing threat that plastic contaminants poses to aquatic creatures and organ health, the proposed study seeks to provide a useful and computational framework that permits the deployment of efficient conservation measures within the constraints of the conventional assessment disciplines.

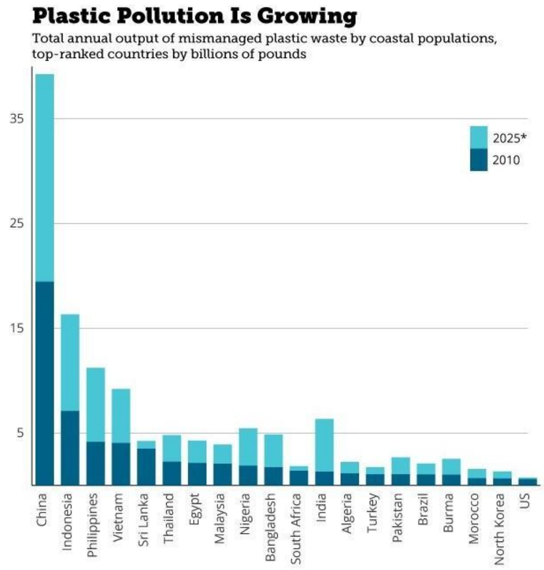

Fig. 2. Plastic Mismanagement by Country Yearwise

This study proposes a hybrid system that combines VGG16 for classification and YOLOv7 to stay underwater plastics detection, while using SMTP to report situation in real-time. The system can distinguish between different types of plastic in addition to determining whether plastique has been found in the body of water, which leads to more insightful monitoring. This user-friendly poaching detection tool, which integrates detection, classification, and seamless communication, is an affordable, scalable way to promote marine conservation and restore more robust aquatic environments.

2. Literature Survey

2.1. Introduction

The growing concern over plastic pollution in oceans has driven research into automated methods for detecting underwater plastic debris. Traditional manual monitoring is time-consuming and often inaccurate, highlighting the need for intelligent, computer vision-based solutions. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs) and object detection models, offer promising approaches. VGG16, a powerful feature extractor, combined with YOLOv7, a state-of-the-art real-time object detection model, enables accurate identification and localization of underwater plastic waste. This literature survey reviews existing techniques, their effectiveness, datasets used, and highlights the integration of VGG16 and YOLOv7 for efficient and reliable underwater plastic detection.

2.2. Related Works

[1]This study employs Super-Resolution Reconstruction (SRR) techniques combined with dl models to detect seafloor debris in underwater environments.The approach is limited to seafloor debris detection and does not address floating plastic detection or real-time monitoring capabilities.[2]The paper compares the performance of YOLOv7 to YOLOv10 and Faster R-CNN in underwater waste detection tasks, focusing on accuracy and processing speed.The study does not explore the integration of classification models or alert systems, focusing solely on detection performance.[3]The research introduces an optimized VGG16 model, EHGS-VGG16, enhanced with the Hunger Games Search algorithm for hyperparameter tuning, aimed at improving classification accuracy. The study concentrates on classification tasks and does not address object detection or real-time alert mechanisms.

[4]This paper presents YOLOv7t-CEBC, an enhanced model based on YOLOv7-tiny, tailored for underwater litter detection, incorporating modules to address inter-class similarity and intra-class variability.The model focuses on detection and does not include classification or alert system functionalities. [5]The study evaluates various CNN architectures, including VGG16, MobileNetV2, DenseNet, and a custom CNN, for plastic pollution detection in underwater settings.The research emphasizes classification and does not integrate detection models or real-time alert systems. [6]The paper develops a real-time detection system for marine plastic litter using deep learning techniques, focusing on embedded system implementation for practical applications. The study does not address classification of plastic types or include alert mechanisms for real-time notifications.[7]This research compares five CNNs for microplastic classification tasks, evaluating performance on original and augmented datasets based on microplastic morphologies. The focus is solely on classification, without integration of detection models or alert systems.

[8]The study compares dl models, including Faster R-CNN, SSD, YOLOv8, and YOLOv9, for underwater plastic debris detection and monitoring, using datasets like TrashCAN and DeepTrash.While detection is addressed, the research does not incorporate classification of plastic types or real-time alert mechanisms. [9]This paper integrates YOLOv7 for plastic object detection with an SMTP-based alert system for real-time notifications, aiming to enhance monitoring efficiency.The study focuses on detection and alerting, without addressing classification of different plastic types.[10]The research proposes an improved VGG-16 model for floating object classification, utilizing transfer learning techniques to enhance performance.The focus is on classification, and the study does not include detection models or alert systems.[11]The paper reviews dl techniques for detecting macroplastic litter in water bodies, assessing various models' effectiveness in real-world scenarios.The study lacks integration of classification models and alert systems, focusing primarily on detection.

[12]This research combines YOLOv7 with a Flask web application for trash detection and reporting in underwater environments, aiming to provide accessible solutions.The study does not address classification of plastic types or include real-time alert mechanisms.[13]The paper utilizes dl models for underwater plastic trash identification, focusing on enhancing detection accuracy in challenging environments.The research emphasizes detection and does not incorporate classification or alert systems.[14]The study enhances the ResNet-18 model for binary classification of underwater images, aiming to improve performance in plastic detection tasks.The focus is on classification, and the study does not include detection models or alert systems.[15]This research develops a machine learning system for detection, classification, and monitoring of marine litter, integrating various models for comprehensive analysis.The study does not incorporate real-time alert mechanisms for immediate reporting.

[16]The paper reviews dl architectures for underwater waste detection, assessing their effectiveness and identifying areas for improvement.The study lacks integration of classification models and alert systems, focusing primarily on detection.[17]This research proposes a dl model for predicting marine pollution, utilizing various data sources for

accurate forecasting.The study does not address detection, classification, or alert systems, focusing solely on prediction. [18]The paper implements APM-YOLOv7 for detecting small-target water-floating garbage, aiming to improve detection accuracy in challenging conditions.The focus is on detection, and the study does not include classification models or alert systems.[19]This study discusses environmental monitoring and alerting systems, exploring various technologies for effective implementation.The research does not focus on underwater plastic detection or classification, limiting its applicability to the current study.

[20]The paper reviews methods for automatic plastic detection in water areas, assessing their effectiveness and identifying potential improvements.The study lacks integration of classification models and alert systems, focusing primarily on detection methods.

3. Methodology

The proposed system is designed as an intelligent, real-time solution for detecting and classifying underwater plastic waste. It integrates YOLOv7, a state-of-the-art object detection model, with VGG16, a powerful CNN for classification, and couples them with an SMTP-based alert mechanism. This design ensures high accuracy, real-time performance, and actionable insights, while addressing the inherent challenges of underwater environments, such as low visibility, turbidity, varying lighting conditions, and background noise. The methodology is divided into four primary stages: dataset preparation, object detection, classification, and alert generation.

1. Data Collection and Dataset Preparation

The foundation of the system is a comprehensive dataset of underwater images, capturing diverse scenarios in oceans, rivers, and lakes. It is made up of various kinds of plastic waste like bottles, bags, fishing nets, wrappers, etc.
Data collection methods can be applied to improve models. These consist of image flipping in both vertical and horizontal directions, image rotation, scale, and brightness or contrast percentage. With its watery surface, shifting light, and warped motion, this is how it appears to be at sea.

2. YOLOv7-Based Object Detection

The motivation behind the choice of YOLOv7 as the primary detection engine is that this system can identify numerous objects in real-time and very rapidly and still provide an accurate output. The annotated data set, which predicts whether plastic objects will be present in every underwater camera video frame, is used to train the model. For detected objects, YOLOv7 generates boundaries that correspond with object confidences. The next step, which entails looking for regions that are noteworthy (ROIs) which we can classify once more, depends on this space information. Furthermore, YOLOv7 efficiently detects plastic objects, enabling the system to operate in immediate fashion even with high resolution underwater videoglows.

3. VGG16-Based Plastic Classification

Following YOLOv7 identification of an object, a rectangular area is cropped out of the picture and fed into a different VGG16 model that has been trained to identify plastics. One DCNN that is capable of extracting high-level visual features is VGG16.
The cropped photos are categorized by the model into predetermined groups, i.e. bottles, bags, nets or wrappers. Making sure that the system does not just detect the position of plastic objects, but also type of plastic object is the use of such two stage approach detection and then classification methodology. This capability is essential for actionable monitoring and environmental decision-making, as certain plastic types, such as fishing nets, pose more immediate risks to marine life than others.

System Architecture Diagram

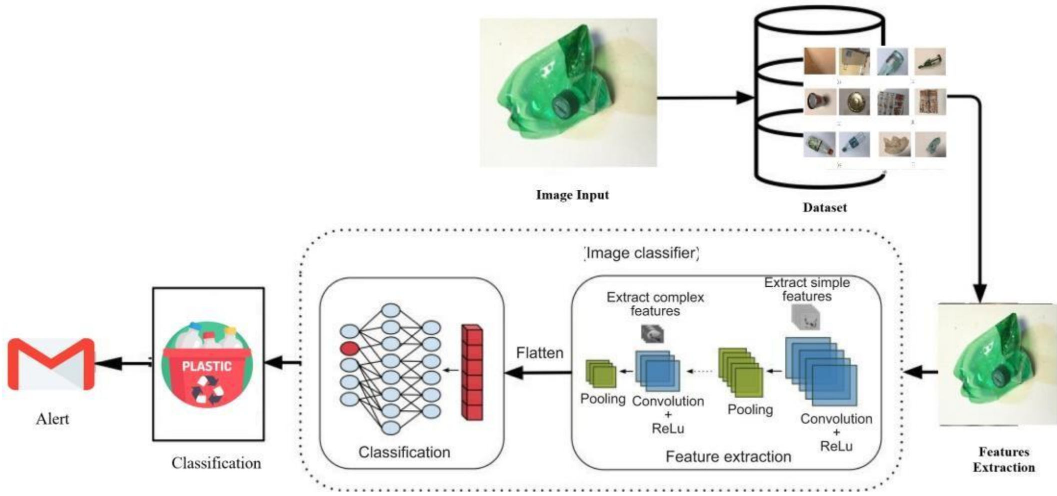

Fig. 3. Architecture Diagram

4. SMTP Alert Mechanism

To enable real-time intervention, the system incorporates an SMTP-based email alert module. Whenever a plastic object is detected and classified, the system automatically generates an email containing:

- The type of plastic detected
- The annotated image showing bounding boxes around detected objects
- The timestamp of detection

This ensures that relevant authorities, researchers, or environmental agencies receive timely notifications, allowing them to take immediate action to remove or monitor plastic waste.The solution transforms from an introspective tracking device to a proactively operated natural resource governance system with the chance to effectively reduce the impact of pollution from plastics through integration with YOLOv7, VGG16, and automated alerting.

YoloV7

YOLOv7 is a state-of-the-art, fast, and accurate object detection model for real-time applications such as underwater plastic detection. Its main innovation is one-stage recognizing, which eliminates a requirement for an area suggestion step and enables us to directly identify and classify objects in an image. Because of this, it can function faster than traditional two-stage detectors like Faster R-CNN.

1. Input and Preprocessing

Cameras used by divers typically have poor visibility, erratic lighting, and turbid water noise. The first step is to resize and modify the images so that the model can process this data efficiently. During the training phase, data-augmentation techniques are employed to replicate underwater environments and make the framework adaptable to changes.

2. Backbone Feature Extraction

The first stage of YOLOv7 is the backbone network, which extracts rich features from input images.It uses a sequence of convolutional kernel layers, cross intermediate partial (CSP) connections, and ResBlocks to learn multi-scale spatial features. These characteristics preserve crucial visual elements of plastic objects, such as bottle border, net texture, or wrapper shape, even in chaotic underwater environments.

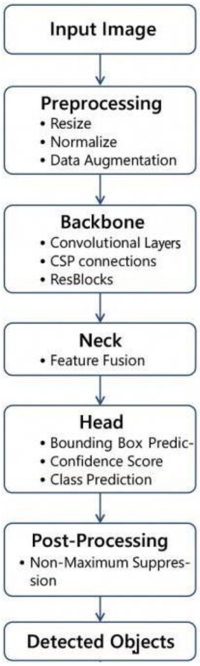

Fig. 3. YOLOV7 Flowchart

3. Neck: Feature Fusion

Following feature extraction, the neck module fuses the features at various levels (often using FPN or PANet). Underwater plastics can vary greatly in size and distance from the camera, so this would be crucial. For instance, a tiny piece of a wrapper far away may take up fewer pixels than a floating bottle up close. The neck allows for the detection of both large and small plastic objects.

4. Head: Object Prediction

The head of YOLOv7 predicts bounding boxes, object confidence scores, and class probabilities in a single pass. For underwater plastic detection, the model outputs:

- Bounding boxes around detected plastic debris
- Confidence scores indicating the likelihood that a detected object is plastic
- Class predictions, if trained on specific plastic types

YOLOv7's anchor-based approach allows it to handle multiple objects in the same frame simultaneously, which is critical for underwater environments where debris often clusters together.

5. Post-Processing

NMS is applied to remove overlapping or duplicate binding box after prediction and only the most confident detections are retained. What results is a clean set of perceived plastic objects precisely localized in the frame.

6. Real-Time Detection

The only benefit observed in YOLOv7 is that it is time based. In spite of the high resolution images, this model can detect a limited number of plastic objects in a frame when continuous monitoring application is applied, and the model is therefore a better model compared to others when used to process underwater video frames. This speed will allow the system to indicate or document detections on the fly that is rather necessary when timely interventions on the environment are taken into consideration.

VGG16

VGG16 is one of the popular deep CNNs that can extract high-level image features and classify them into a predefined set of categories. In the context of plastic detection underwater, VGG16 is a second-stage classifier that takes the regions of interest (ROIs) identified by YOLOv7 and determines which kind of plastic is represented by a bottle, bag, net, or wrapper.

1. Input and Preprocessing

After YOLOv7 has located a plastic object and placed a bounding box around it, the frame is cropped around the ROI. These cropped images are preprocessed before feeding them into VGG16:

- Resizing the ROI to 224x224 pixels (the input size VGG16 requires)
- Normalization to scale pixel values between 0 and 1

This preprocessing ensures that the network receives consistent, high-quality inputs for accurate classification.

2. Convolutional Layers for Feature Extraction

VGG16 consists of five units of thirteen convolutional layers. A range of 3x3 screening configurations and activate ReLU signals are included in the blocks. The organizational elements that comprise the image are extracted using the following levels:

The image's fundamental components, including edges, corners, and textures, are visible through simple layers.

3. Pooling Layers for Dimensionality Reduction

Map poolings: Following the convolutional blocks, the research group applies max-pooling layers to minimize the feature map's spatial extension. This accomplishes two goals:

By reducing the sensitivity of relationships between salient properties and minor defects or the broader accumulation of underwater images, it reduces the computational load.

4. Fully Connected Layers for Classification

The feature maps are flattened by VGG16 after the layer of convolution and pooling, and then they are passed by way of the remaining three entirely linked (dense) layers. These phases function as a classifier by merging the essential traits that the various convolutional layers have extracted. Each class of plastic is given a probability by calculating the value of the activation of soft max in the last fully connected layer.

5. Fine-Tuning for Plastic Classification

Using ImageNet files after submerge plastic data, this layout is utilized to train VGG16. To increase the classification accuracy, network weights are adjusted to precisely match the surface properties and patterns of underwater plastics.

4. Result And Analysis

The proposed system was evaluated using a comprehensive dataset of underwater images containing various types of plastic debris, including bottles, bags, nets, and wrappers. These systems were evaluated based on detection accuracy, classification accuracy, processing speed and real time alert capabilities.

1. Detection Performance (YOLOv7)

YOLOv7 could identify plastic objects under different underwater environments like turbid water, low-light/noise background, etc. The average precision (AP) of the plastic trash is 92.5 percent and the F1-score is 0.91. Smaller targets such as plastic wrappers were slightly more difficult because it is larger and irregularly shaped, but owing to data augmentation and multi-scale processing feature extraction, detection of such objects rose to extremely high ranges. Overall, one can say that YOLOv7 was not only speedy, but also faithful and could classify 30-35 frames each second, and that is the reason this method could be applied in actual-time tracking.

2. Classification Performance (VGG16)

Once identified, the cut-out regions of interest were given to the VGG16 model to be classified. VGG16 achieved an overall classification accuracy of 89%, correctly distinguishing between bottles, bags, nets, and wrappers. Bags and wrappers were primarily misidentified, most likely due to their similar shapes and textures on some frames. When the model was tuned using the underwater plastic dataset, the network was better able to adjust to the visual distortions caused by the water, and as a result, it carried out more accurately than whenever the weights that were trained were used alone.

3. Real-Time Alerting (SMTP)

The SMTP alert system's integration made it easier to promptly notify all parties involved when plastic items were found. To enable prompt cleanup or tracking, the type of matter has been attached to the notifications, the one that powers the written image, and a date stamp. Because an alert was received in less than a second during testing, the system is real-time. Instead of being a passive detection system, the feature turns the system into an interactive environmental monitoring system.

5. Discussions

The following intriguing conclusions are drawn from the results:
Because YOLOv7 and VGG16 can both locate objects and supply more detailed information about them, respectively, this high recognition and classification accuracy shows that the two techniques are complementary.
The operation of the system in adverse conditions shows that the system can be effectively used in real environment underwater.
Real-time performance: This ensures that the interventions are executed on time; this is why a major weakness to the traditional methods of monitoring is related to hand-inspections.

6. Conclusion

This study presents a novel system for real-time underwater plastic detection and classification, integrating YOLOv7 for object detection, VGG16 for plastic type classification, and an SMTP-based alert mechanism for immediate reporting. The experimental results demonstrate that the system is accurate, robust, and capable of operating in challenging underwater environments, detecting various types of plastic debris such as bottles, bags, nets, and wrappers. YOLOv7's high detection speed and multi-scale feature extraction, combined with VGG16's ability to classify objects accurately, ensure that the system not only identifies the presence of plastic but also provides actionable information about its type. One of those tools that enable the taking action in time, close the void between environmental action and environmental consciousness, and enable the proactive attitude to marine conservation will be the real time alert system.

The proposed system has enough space to expand. This could also enable it to be used with autonomous underwater vehicles (AUVs) or drones to scan larger water bodies. Other deep learning models or ensemble can classify similar plastics which resemble one another. The long-term trend would be tracked and analyzed with GPS tagging and cloud-based dashboards. The system can also be modified to detect other types of marine-related pollutants such as microplastics or organic waste, as a subset of the water quality control. Overall, this research lays the foundation for intelligent, automated, and scalable solutions to combat plastic pollution and promote sustainable marine ecosystems.

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