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# Water Trash Detection System: An Innovative Approach to Monitoring Aquatic Pollution

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**Abstract**: *Water pollution caused by non- biodegradable materials, especially plastics, poses a significant threat to aquatic ecosystems. This study introduces a novel approach to identifying and categorizing waste in water environments through advanced machine learning methods. The proposed Water Trash Detection System (WTDS) integrates You Only Look Once (YOLO) for rapid object detection and Convolutional Neural Networks (CNNs) for categorization of waste types. Capable of analyzing both static imagery and live video feeds, the system can accurately detect items such as plastic bottles, bags, and fishing-related debris. WTDS also provides comprehensive reports on detected waste, supporting environmental agencies and researchers with crucial data for tracking and mitigating water pollution. By combining real- time detection with high classification precision, the system offers a practical solution for sustainable environmental monitoring and management.*

**Keywords**: Water contamination, aquatic debris detection, YOLO, convolutional neural networks, machine learning, real-time monitoring, waste classification, environmental protection, computer vision, image analysis, sustainability

## I. INTRODUCTION

Water pollution has become one of the most pressing environmental challenges of our time, largely due to the widespread accumulation of non-biodegradable waste—particularly plastics— in oceans, rivers, and lakes. Annually, millions of tons of plastic enter aquatic environments, endangering marine organisms, disrupting ecosystems, and posing risks to human health. As plastics degrade, they release hazardous substances and microplastics, which are consumed by aquatic species and eventually enter the human food chain. Larger debris, such as plastic containers and fishing gear, physically obstruct marine life, leading to entanglement, injury, and a decline in biodiversity.

To combat this growing problem, various technological solutions have been explored—from large-scale cleanup initiatives to sophisticated monitoring tools. However, challenges remain. Traditional cleanup efforts are labor-intensive, costly, and geographically limited, often unable to address pollution in remote or expansive regions. Manual observation and detection of waterborne waste are similarly constrained by time, resources, and the vast scale of affected ecosystems, making continuous surveillance impractical.

In light of these limitations, automated, technology-driven approaches offer promising alternatives. The Water Trash Detection System (WTDS) introduces an intelligent, machine learning-based solution for the detection and classification of aquatic waste. Leveraging You Only Look Once (YOLO)—a high-speed, real- time object detection algorithm—and Convolutional Neural Networks (CNNs), the WTDS effectively identifies and categorizes various types of floating debris. YOLO enables rapid and accurate detection from both still images and video streams, allowing the system to recognize pollutants such as plastic bottles, bags, and fishing equipment under varying environmental conditions.

To complement detection, CNNs are used to classify waste into specific categories, offering detailed insight into the composition of pollution. This categorization helps inform actionable strategies for cleanup and resource allocation. The system is capable of analyzing live video streams in real time, enabling continuous monitoring of water bodies such as rivers, lakes, and coastal areas. Such capabilities reduce reliance on manual labor while enabling broad and sustained surveillance of water quality.

Ultimately, the WTDS addresses a critical gap in current environmental management by combining automation, scalability, and precision. Through real-time detection and classification, the system enhances pollution monitoring efforts and provides valuable data to environmental agencies and decision-makers, supporting more effective and targeted conservation practices.

## II. RELATED WORK

### A. Machine Learning in Environmental Monitoring

Recent advances in deep learning have demonstrated significant potential for environmental monitoring. For example, Li et al. (2021) implemented Convolutional Neural Networks (CNNs) for land-based waste detection, highlighting the effectiveness of deep learning in classifying solid waste. However, the transition of these techniques to aquatic environments, particularly for detecting submerged or underwater waste, remains a major challenge. Similarly, Zhou et al. (2020) leveraged satellite imagery to identify oceanic debris, but their approach struggled with detecting smaller or partially submerged objects, especially under murky water conditions.

### B. Real-Time Detection Using YOLO

The YOLO framework has gained attention for its speed and accuracy in object detection tasks. Prakash et al. (2020) applied YOLO to drone-captured videos for identifying large marine debris, demonstrating real- time capabilities. Nonetheless, its effectiveness diminished when detecting waste submerged below the water's surface. In another study, Yuan et al. (2021) adapted YOLO for tracking floating debris in urban waterways. Although their approach achieved reasonable results, its accuracy dropped significantly in low-visibility environments, such as turbid or sediment-rich waters.

### C. Waste Classification with CNNs

CNNs have also been widely adopted for classifying aquatic waste. Shen et al. (2021) employed CNN architectures to analyze drone images of marine pollution, yielding high classification accuracy for surface-level debris. However, the system struggled under dynamic conditions, such as moving water and partially hidden waste. Bui et al. (2019) focused on detecting plastic waste using CNNs, achieving success in identifying visible surface-level debris, but encountering limitations with submerged or distorted objects.

### D. Processing Real-Time Video Streams

Integrating detection algorithms with video stream processing has been explored to facilitate continuous environmental monitoring. Vidyasagar et al. (2020) combined YOLO with CNNs for real-time trash detection in rivers, but scalability remained a concern for broader geographic coverage. Rahman et al. (2020) introduced a hybrid model by integrating YOLO with Long Short-Term Memory (LSTM) networks to improve temporal consistency across frames. While this improved detection stability over time, it still faced challenges in handling large-scale environments.

### E. Persistent Challenges in Aquatic Waste Detection

Despite these advancements, aquatic waste detection continues to face several technical hurdles. One key issue is the accurate identification of submerged objects, which conventional vision-based methods often fail to address. Tian et al. (2020) attempted to mitigate this by integrating infrared sensing with CNNs, offering improved detection in certain underwater scenarios. Additionally, environmental conditions such as water turbidity, fluctuating lighting, and surface movement significantly impact detection reliability. Studies suggest that overcoming these limitations may require adaptive algorithms or the fusion of multiple sensing modalities, including infrared and sonar technologies.

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## III. DATASET

This study focuses on classifying recyclable materials to support automated and efficient waste management. Initially, we used the TrashNet dataset, which contains six categories—glass, paper, cardboard, plastic, metal, and general waste—with images captured against a white background under varied poses and lighting. Each image is resized to 512 × 384 pixels, and the dataset size is around 3.5 GB.

To improve the system's real-world adaptability, we also incorporated the Waste in Water dataset from Roboflow Universe. This dataset includes images of waste floating in water, offering diverse backgrounds and environmental conditions. Combining both datasets allows our model to perform effectively in both controlled and natural settings, enhancing classification accuracy and robustness.

- Dataset Splitting Strategy: To ensure fair evaluation and avoid overfitting, the annotated dataset was divided into three parts:
- Training Set (70–80%): Used to train the YOLO model by learning object features and patterns.
- Validation Set (10–15%): Used during training to fine-tune hyperparameters and monitor model performance.
- Test Set (10–15%): Kept separate from training and validation, used only for final performance evaluation on unseen data.

## IV. METHODOLOGY

### A. Data Collection

For effective training of the custom YOLO model in the Water Trash Detector project, a diverse and representative dataset was compiled.

#### 1. Sources:

Public Datasets: Open-source datasets related to trash detection (e.g., TACO) were used to provide a base of annotated images across various conditions.

Custom Data Collection: Images and videos were captured from targeted environments to ensure relevance and diversity.

### B. Image Preprocessing

Before input images are passed to the YOLO model, they are preprocessed to meet model requirements. These steps ensure uniformity and enhance training efficiency.

#### 1. Color Space:

Images are converted to the RGB format, which is the standard for computer vision tasks due to its compatibility with deep learning models.

#### 2. Resizing and Normalization:

- Resizing: All images are resized to fixed dimensions (e.g., 640×640, 416×416) expected by the model. Padding is applied where necessary to maintain aspect ratio.
- Normalization: Pixel values are scaled to the range [0, 1] by dividing by 255, ensuring consistent input scale and supporting faster convergence during training.

These preprocessing tasks are generally automated by frameworks like Ultralytics YOLO, but remain essential for consistent and accurate model performance.

### C. Feature Extraction

In the Water Trash Detector project, which employs a YOLO-based deep Convolutional Neural Network (CNN), feature extraction is handled automatically as part of the model's internal learning process.

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**A. Hierarchical Feature Learning**

YOLO learns features directly from input images during training. Instead of manual feature engineering, the network adjusts its weights to identify the most relevant patterns for object detection. This automation enhances efficiency and accuracy.

**B. Multi-Level Feature Representation**

**Shallow Layers (Early Stages):**

These layers detect basic visual elements such as edges, textures, and color patterns. These features are general and form the foundation for more complex representations.

**Intermediate Layers:**

Here, combinations of low-level features are formed into object parts or more detailed patterns (e.g., shapes of plastic bottles, textures of bags). These layers enhance the model's understanding of specific object components.

**Deep Layers (Later Stages):**

The final layers capture high-level, abstract features that help differentiate specific garbage types like styrofoam, cans, or plastic. These layers contribute directly to object classification and localization.

**D. Model Architecture**

The Water Trash Detector system relies on a custom-trained YOLO object detector, chosen for its real-time performance and accuracy in detecting marine debris.

**1. Framework and Version**

The model is built using the Ultralytics YOLO framework, based on a modern version such as YOLOv5 or YOLOv8. This framework is widely adopted due to its active development, availability of pre-trained models, and user-friendly tools for custom training and deployment.

**2. Architecture Overview**

YOLO is a single-stage object detector, meaning it performs both object localization and classification in one forward pass of the network. This is in contrast to two-stage detectors, which separate these tasks.

**Key Features:**

- High Speed: Single-pass detection enables fast inference, ideal for real-time monitoring.
- Competitive Accuracy: Modern YOLO variants achieve strong performance across diverse detection tasks.
- End-to-End Learning: The model jointly learns to identify object locations and categories, streamlining the training process.

**E. Training Strategy**

To train the custom YOLO model for detecting aquatic waste, a structured training approach was followed to optimize accuracy and efficiency.

**1. Transfer Learning**

Training began with pre-trained weights (e.g., from the COCO dataset) to leverage generalized visual knowledge.

Benefits:

- Faster convergence due to existing feature extraction capabilities.
- Improved generalization on limited data.
- Reduced dataset size requirement for effective training.

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**2. Training Hyperparameters**

The model training process was guided by carefully chosen hyperparameters to ensure stable convergence and efficient learning:

- Epochs: The training spanned 100 epochs, with performance monitored on a validation set to avoid overfitting.
- Batch Size: Selected based on the available GPU memory, balancing computational efficiency and gradient stability.
- GPU Acceleration: Training was conducted using high-performance GPUs (e.g., NVIDIA Tesla T4 or V100), which significantly reduced training time and enabled large-scale parallel computations.

**F. System Integration and Deployment**

The trained YOLO model was integrated into the OceanWasteTracker web application using the Flask framework to enable real-time trash detection via a user-friendly interface.

**1. Model Integration:**

The custom-trained model (.pt file) was loaded at runtime using the Ultralytics YOLO library, enabling backend access for inference tasks.

**2. User Input Interface:**

The Flask-based web UI allows users to upload images or videos. These inputs are handled via POST requests and temporarily stored for processing.

**3. Inference Pipeline:**

Uploaded media undergoes preprocessing (resizing, normalization) consistent with training. YOLO performs detection and returns object classes, confidence scores, and bounding box coordinates. Results are parsed, filtered (e.g., confidence > 0.25), and formatted for storage.

**4. Database Storage:**

Detection results are stored using SQLite, accessed via SQLAlchemy ORM. A structured table stores attributes like trash_type, confidence, coordinates, timestamp, and media_filename.

**5. Visualization & Reporting:**

Detected objects are visualized using OpenCV, displaying bounding boxes and labels on images/videos. The system also supports reporting via:

- Trash-type distribution charts
- Downloadable summaries in formats like CSV

## V. RESULTS

This section outlines the evaluation of the custom YOLO model developed for the Water Trash Detection System. It presents both quantitative performance metrics on a reserved test dataset and qualitative insights derived from real-world testing scenarios.

**Quantitative Performance Evaluation**

To assess the generalization capability of the model, a held-out test set was used to compute standard object detection metrics. These include precision, recall, F1-score, and mean Average Precision (mAP) at different IoU thresholds. The training was performed over 36 epochs, and the metrics reported here correspond to the final model checkpoint, evaluated at a confidence threshold of 0.25.

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Table 1: Performance Metrics

| Metric | Value |
|---|---|
| Precision (P) | 0.842 |
| Recall (R) | 0.786 |
| F1-Score | 0.813 |
| mAP@0.5 | 0.871 |
| mAP@0.5:0.95 | 0.671 |

These results demonstrate that the model is both accurate and reliable in detecting various types of floating garbage in aquatic environments. A high precision (0.842) indicates that most detections made by the model are correct, while the recall score (0.786) confirms that it successfully identifies the majority of relevant objects. The mAP@0.5 of 87.1% reflects strong localization and classification performance at a standard IoU threshold. Furthermore, the mAP@0.5:0.95 value of 67.1% confirms consistent accuracy across stricter IoU ranges, underscoring the robustness of the model

## VI. CONCLUSION

The Water Trash Detection System successfully demonstrates the application of deep learning and computer vision for environmental monitoring. By leveraging a custom-trained YOLO model, the system can accurately detect and classify various types of floating waste in aquatic environments. The integration of this model within a user- friendly web application makes the solution accessible for real-time detection and long-term tracking of pollution patterns.

The model achieved strong performance metrics, including high precision and mean average precision, which indicate its reliability in real- world scenarios. Additionally, the use of transfer learning and GPU-accelerated training significantly improved the training efficiency and overall accuracy, even with a moderate-sized dataset.

Overall, this system provides a practical approach to support efforts in marine conservation, enabling data-driven decision-making and community engagement. Future enhancements may include expanding the dataset, improving detection under varying lighting and water conditions, and deploying the model on edge devices for on-site monitoring

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