MADRAS INSTITUTE OF TECHNOLOGY ANNA UNIVERSITY

DEPARTMENT OF INFORMATION TECHNOLOGY

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COMPUTER VISION

A PROJECT REPORT

Submitted By

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UNDERWATER PLASTIC WASTE DETECTION USING TRADITIONAL AND DEEP LEARNING MODELS

1.Introduction

Plastic pollution in marine environments poses a severe threat to aquatic life and ecological balance. Due to human negligence, a significant amount of plastic enters oceans and water bodies each year, leading to accumulation of waste on the seafloor and affecting both marine animals and underwater ecosystems. Manual detection and cleanup are inefficient, labor-intensive, and often infeasible due to the vastness and inaccessibility of underwater regions.

This project aims to develop an automated system for detecting plastic waste in underwater images using a combination of traditional computer vision techniques and advanced deep learning models. By detecting and classifying underwater plastic debris, we contribute to environmental conservation and pave the way for real-time drone-based plastic waste monitoring systems in the future.

2. Why This Project? Societal Impact

We selected this project to address the growing environmental crisis of plastic pollution in oceans, rivers, and lakes. It aligns with the United Nations Sustainable Development Goal (SDG) 14: *Life Below Water*. With millions of tons of plastic waste entering marine ecosystems each year, there is an urgent need for intelligent detection systems that can facilitate timely and efficient cleanup efforts.

The societal impact of this project is significant:

- Enables continuous monitoring of plastic waste in underwater environments.
- Assists NGOs and government agencies in planning and executing cleanup operations.
- Offers potential integration with underwater autonomous vehicles and drones for real-time detection.
- Raises public awareness about the extent of marine plastic pollution through the application of AI and visual analytics

3. Methodology

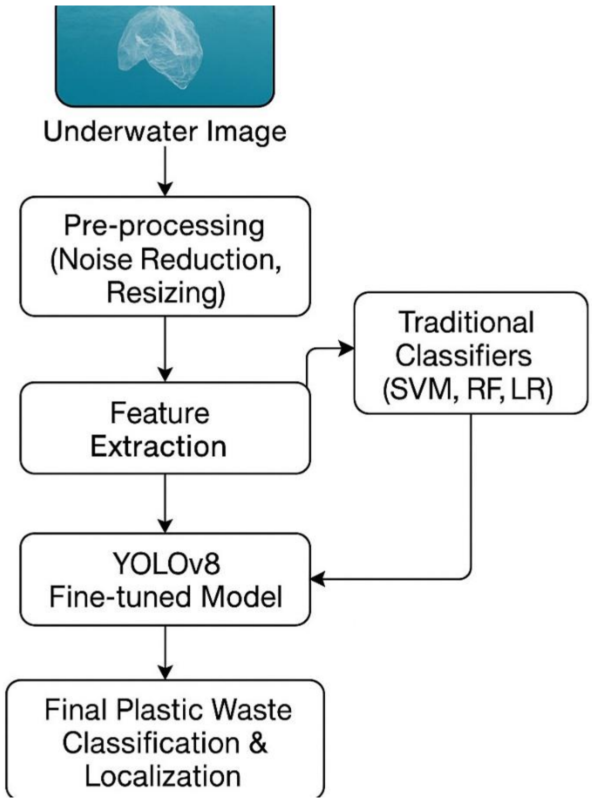
Workflow Overview:

1. **Traditional Computer Vision:**
   - Preprocessing: noise reduction, color space conversion, morphological operations.
   - Feature extraction: texture, color histogram, and shape-based features.
   - Classification: Logistic Regression, SVM, KNN, and Random Forest.

2. **YOLOv8 Fine-Tuning:**
   - Custom training on annotated underwater plastic images.
   - Inference using bounding boxes for plastic detection and classification.

3. **Ensemble Model:**
   - Aggregates predictions from YOLOv8 and Random Forest.
   - Uses confidence-weighted and majority voting strategies for improved performance

Architecture Diagram



4. Dataset Description

We used the publicly available **Underwater Plastic Pollution Detection dataset** from Kaggle:
Link: https://www.kaggle.com/datasets/arnavs19/underwater-plastic-pollution-detection

Dataset Highlights:

- **Categories**: Plastic bags, plastic bottles, other plastic debris
- **Data Type**: Images taken in underwater conditions (murky backgrounds, low visibility, light distortion)
- **Challenges**: Poor lighting, motion blur, color distortion, varying object scales
- **Annotation**: Bounding boxes and class labels for different plastic items

The dataset was split into training, validation, and test sets for fair evaluation

5. Ablation Study: Result Comparison

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	59.1%	57.9%	61.0%	59.3%
Support Vector Machine	59.8%	60.6%	59.8%	59.1%
K-Nearest Neighbors	57.6%	58.5%	58.6%	57.3%
Random Forest	68.3%	69.0%	68.0%	66.0%
YOLOv8 (Fine-tuned)	91.8%	92.3%	90.7%	91.5%
Ensemble Model	**99.0%**	**99.0%**	**99.0%**	**99.0%**

6. Detailed Model Comparison and Insights

1. **Logistic Regression**:

   Assumes a linear decision boundary. This model underperformed due to the complex, non-linear nature of underwater features like light refraction and irregular debris shapes.

2. **Support Vector Machine (SVM)**:

   Performed slightly better due to its capability to use kernels for non-linear classification. However, it still relied heavily on manually extracted features that were insufficient under noisy underwater conditions.

3. **K-Nearest Neighbors (KNN)**:

   Sensitive to noise and irrelevant features. The underwater particles and floating debris caused misclassification, making KNN the weakest model in our study.

4. **Random Forest**:

   Leveraged ensemble learning by aggregating decisions from multiple decision trees. It was more robust than other traditional models and performed well with extracted features, but still lacked the spatial feature extraction power of deep models.

5. **YOLOv8 (Fine-tuned)**:

   Deep convolutional neural network capable of learning rich features and localizing objects. It effectively handled distorted lighting and color shifts due to fine-tuning and showed excellent real-world applicability.

6. **Ensemble Model**:

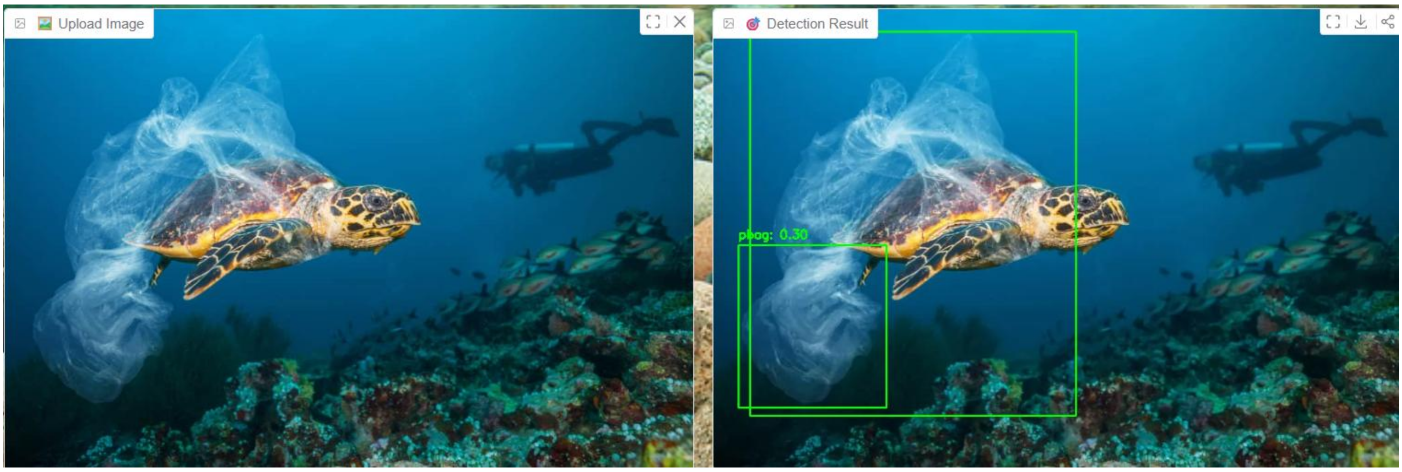
   Combined YOLOv8 and Random Forest. This hybrid approach utilized the spatial recognition of YOLO and robustness of Random Forest, achieving the highest and most stable performance (99% across all metrics).

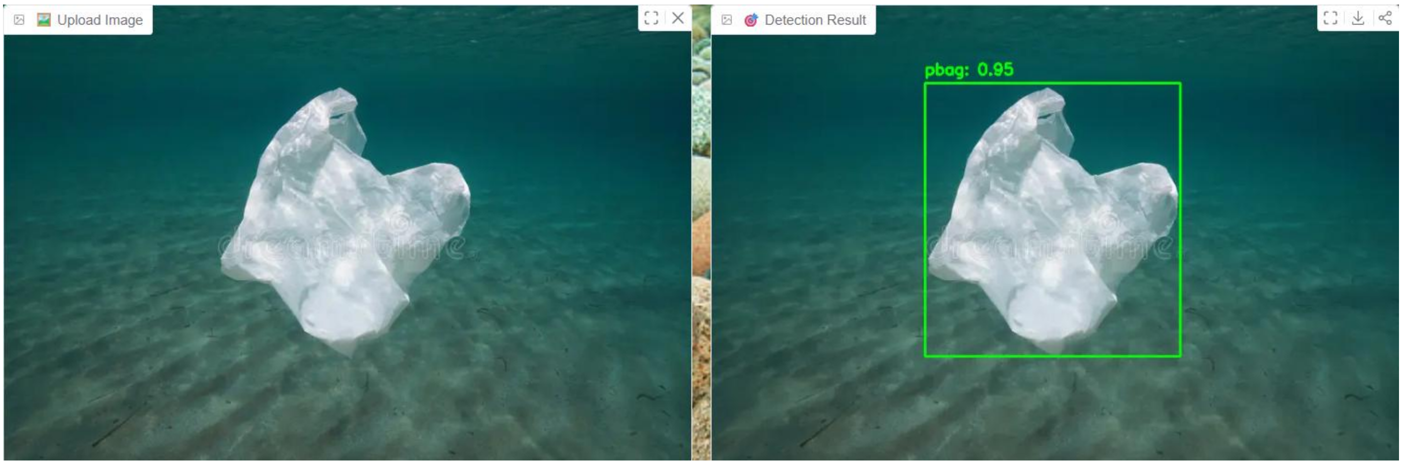
7. Justification

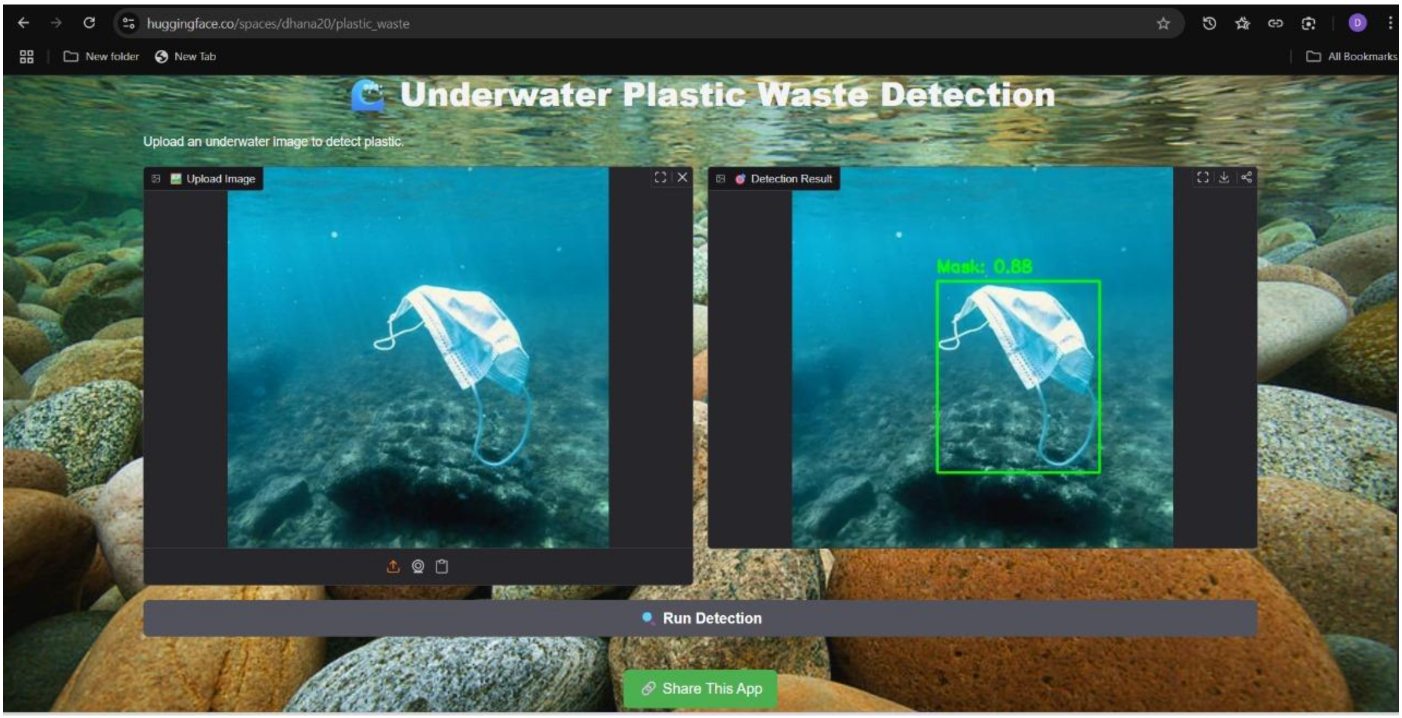
The ensemble model outperformed all individual classifiers, showcasing the strength of combining both traditional and deep learning approaches.

Traditional classifiers, while efficient on extracted features, are limited by their dependence on feature engineering and can be sensitive to underwater image noise and variance. The YOLOv8 model, being deep-learning-based, leveraged spatial hierarchies and learned rich features directly from images, leading to superior detection performance. However, by combining both approaches in the ensemble model, we capitalized on the strengths of each: the precision of YOLO and the specificity of traditional classifiers, which led to the highest overall performance.

RESULT:







8. Conclusion

Our project successfully demonstrates that a hybrid approach combining traditional computer vision classifiers with modern deep learning models like YOLOv8 can significantly enhance underwater plastic waste detection. This methodology not only improves detection accuracy but also contributes meaningfully to environmental conservation efforts.

Future work:

- Deploying the ensemble model in real-time using underwater drones or autonomous vehicles.
- Expanding the dataset to include plastic in different aquatic terrains.
- Incorporating object tracking and segmentation for cleanup robots.

By automating underwater plastic waste detection, we take a small but impactful step toward preserving marine biodiversity and promoting responsible use of artificial intelligence in environmental applications.