
# Aquatic Waste Sorting and Classification Using Image Processing and Detection System Using YOLOV8 Model and Django

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**ABSTRACT**

In waste management, efficient and automated sorting systems are critical in enhancing recycling processes and reducing labor. A real-time waste sorting method has been developed using YOLOv8, a state-of-the-art object detection model, in detecting and classifying plastics, metals, glass, and paper. It works by capturing live video feeds and then processes every frame through YOLOv8 for object detection; it also provides the output through a web interface that has been developed with Django. With YOLOv8's capability of real-time object detection, it can classify waste materials at high speed and accuracy to ensure sorting can be carried out without substantial delays, thereby being suitable for dynamic and high-throughput environments like recycling plants or municipal waste management facilities. The problem of proper waste management is an acute global concern, especially in aquatic ecosystems, where pollution poses significant threats to ecological integrity and public health. This introduces a new approach: front-end development through HTML, CSS, and back-end development using Python language with Anaconda to develop an environment that can be used to deploy an API. The most outstanding feature is giving the system real-time feedback that improves rapid classification without increasing errors in waste sorting. It is designed to be scalable, thus fitting diverse operation settings such as municipal waste management facilities, industrial recycling centers, and even remote aquatic environments.

**Keywords:** Aquatic waste detection, YOLOv8 object detection, Underwater image processing, Real-time waste sorting, Django-based web interface

## Introduction

Waste management is considered to be one of the serious issues in modern times. The day-to-day waste quantity has reached threatening proportions due to the increase in population in towns and expanded industrial activities. Lousy waste management, largely caused by the lack of effective waste sorting and recycling is accelerating environmental problems such as land degradation, water contamination, and emission of gases into the atmosphere. Manual sorting methods, which are still in use, rely on substantial human labor inputs, are slow, and error-prone. Besides that, the process leaves employees vulnerable to toxic wastes, making the system not only inefficient but also unsafe. With the emergence of AI and machine learning, comes the idea of automating waste management systems and improvising them.

Since object detection models are AI technologies, they can look for objects in images or video streams and classify them accordingly, thus promising avenues toward automation of the process of waste sorting. Therefore, if such intelligent systems were combined with scalable software solutions, then it would bring about a revolution in managing waste with much less human effort. The is to develop software-intensive waste sorting using YOLOv8. Initial testing conditions of lighting, water turbidity, and debris obstruction. It makes the solution flexible and accessible by incorporating a user interface that properly allows the interaction of data, supports historical analysis, and enhances reporting. It is an attempt not only to solve the shortcomings of conventional manual sorting but also to make it sustainable through reduced pollution and increased recycling.

### Current Works

The method to analyze using seven underwater image enhancement algorithms representing the state-of-the-art detection model.[1] A Convolutional Neural Network (CNN) starts by applying convolution and pooling operations. These steps help to analyze and break down the input image, identifying and extracting important features such as edges, textures, and patterns, which are crucial for further processing and understanding the image's content. The result of this process is then fed into a fully connected neural network, driving the final classification decision for the input image. The study focuses on evaluating how well min-terms perform in the task of image annotation, particularly for deep-learning applications.[2] It examines their role and effectiveness in accurately labeling and categorizing images, which is a crucial step in training deep learning models for various image recognition and analysis tasks. Besides Mask RCNN, other popular architectures such as YOLO or Retina Net can be used.

1 The potential of deep learning in waste management in densely populated and industrial environments. Most automated sorting systems operate for limited target waste items. Emerging advances and increasing functionalities of robot system components will widen system applicability and increase use cases in the chaotic industrial waste domain. This offered waste sorting and a robust solution for sustainable waste management.
2 To achieve recycling of mixed industrial waste items toward an advanced sustainable society, waste sorting automation by robots is crucial and urgent. The presence of contamination in recycling processing units causes major impacts in the recycling rates,

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Additional material is published online only. To view please visit the journal online.

**Cite this as:** Gayathri J, Yasir Hameed T, Thivakar V, Pranesh Akilan AR and Prabhu V. Aquatic Waste Sorting and Classification Using Image Processing and Detection System Using YOLOV8 Model and Django. Premier Journal of Science 2025;15:100146

**DOI:** https://doi.org/10.70389/PJS.100146

Peer Review
**Received:** 14 August 2025
**Last revised:** 26 September 2025
**Accepted:** 1 October 2025
**Version accepted:** 3
**Published:** 27 December 2025

Ethical approval: N/a
Consent: N/a
Funding: No industry funding
Conflicts of interest: N/a
Author contribution: J Gayathri, T Yasir Hameed, V Thivakar, AR Pranesh Akilan and V Prabhu – Conceptualization, Writing – original draft, review and editing
Guarantor: J Gayathri
Provenance and peer-review: Unsolicited and externally peer-reviewed
Data availability statement: N/a

leading to the rejection of entire loads while waste management. This offered the necessity for robots to recognize the categories, poses, and conditions of different waste items and manipulate them based on the category to be sorted.

3 Insights on the potential of blockchain technology to enhance waste management, addressing issues of manual and centralized systems that are prone to manipulation and failure. This analysis assumes a known geometrical configuration of the rectified camera system. The critical factor limiting the 3D object metric estimation accuracy is the resolution of the computed depth maps of fish. Object-based matching is proposed for underwater object tracking and depth computing to address this issue using reliable convolutional neural networks (CNNs).
4 For each stereo video frame, an object classification and instance segmentation CNN separates the object from its background. The objects are cropped and then matched using sub-pixel disparity computation of the video interpolation CNN. To deal with the limitations of distance or range of the low-cost stereo camera system more mechanisms are incorporated to increase accuracy. Three hybrid Classical-Quantum neural networks ResNet50-QCNN, ResNet18-QCNN, and InceptionV3-QCNN have been proposed for underwater quantum-classical Animal Identification and Classification. It significantly lessens the complexity of classical computer processing data by using quantum devices to minimize dimension and denoise data sets.
5 The numerical simulation results demonstrate that the quantum algorithm is capable of effective dimensionality reduction and improves accuracy. To achieve more accurate images and results, it is necessary to expand the training data by adding more image datasets for the instance segmentation neural network. This increase in data will help the network learn a broader range of features, improving its ability to segment and classify objects more precisely.

## Proposed Methodology

The automated aquatic waste detection and sorting system using YOLOv8 is the proposed work that addresses all the barriers associated with waste management since an auto process for waste material segregation and categorization is enabled. By utilizing the cutting-edge object detection model, it helps users identify the type of waste they are dealing with. This advanced technology ensures accurate classification including, recyclable wastes, biodegradable waste, and the type of waste not to recycle. Comparative analysis shows YOLOv8 achievesv 82% mAp compared to 78% for YOLOv5 and 75% for EfficinetDet. So, this system uses YOLOv8 and also this supports suitability for realtime embedde deployment.[3] The basic structure of architecture bases its work on the platform Django. The whole system gives instant feedback. After the removal of waste, it shows the intended category to the users and teaches them how to sort properly.

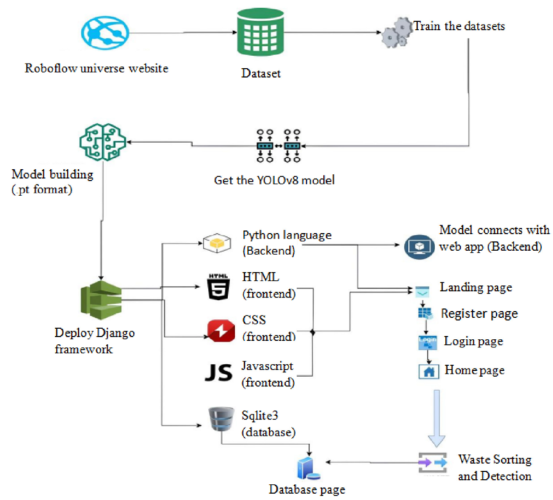


**Fig 1 | System architecture of deployment framework**

This characteristic increases the effectiveness of waste management through reduced errors in sorting and responsible recycling behavior. This system enables a more efficient and environmentally friendly approach toward waste management through the combination of precision capabilities inherent in YOLOv8 with the intuitive interface offered by Django.

Figure 1 shows the overall system architecture. The figure emphasizes the YOLOv8 model pipeline for object detection, integration for data logging and realtime visualizations, The architecture depicts how camera input is processed,results are stored, and presented through the Django interface. Feedback loop and user input flow are also shown to highlight adaptive learning. This system has been developed to identify and categorize underwater waste instantaneously by employing YOLOv8 (You Only Look Once Version 8) and model was trained for 100 epochs with a batch size of 16 and a learning rate of 0.0001.[4] Training was done on an NVIDIA RTX 3060 GPU using Ultralytics PYTorch framework. The training converged after 78 epochs. Yolov8 represents a state-of-the-art deep learning model distinguished for its rapidity and accuracy, rendering it ideally suited for aquatic settings where timely decision-making is essential. It trains the YOLOv8 using a heterogeneous dataset of plastics, metals, and organic materials. Using CNNs, the system can identify and classify different types of waste starting from aquatic images or video streams. The presence of Django helps in web applications which allows users to interact with the data, view visualizations, and generate reports. In addition to enhancing the efficiency of waste classification, this system promotes environmental sustainability through an understanding of waste trends and optimizing recycling efforts as shown in Figure 1. This system architecture with real-time capabilities powered by YOLOv8, is central to automating underwater waste management and the support of ocean conservation efforts.

Figure 2 (a to d) together illustrate the web-based system interface. The automated aquatic waste detection

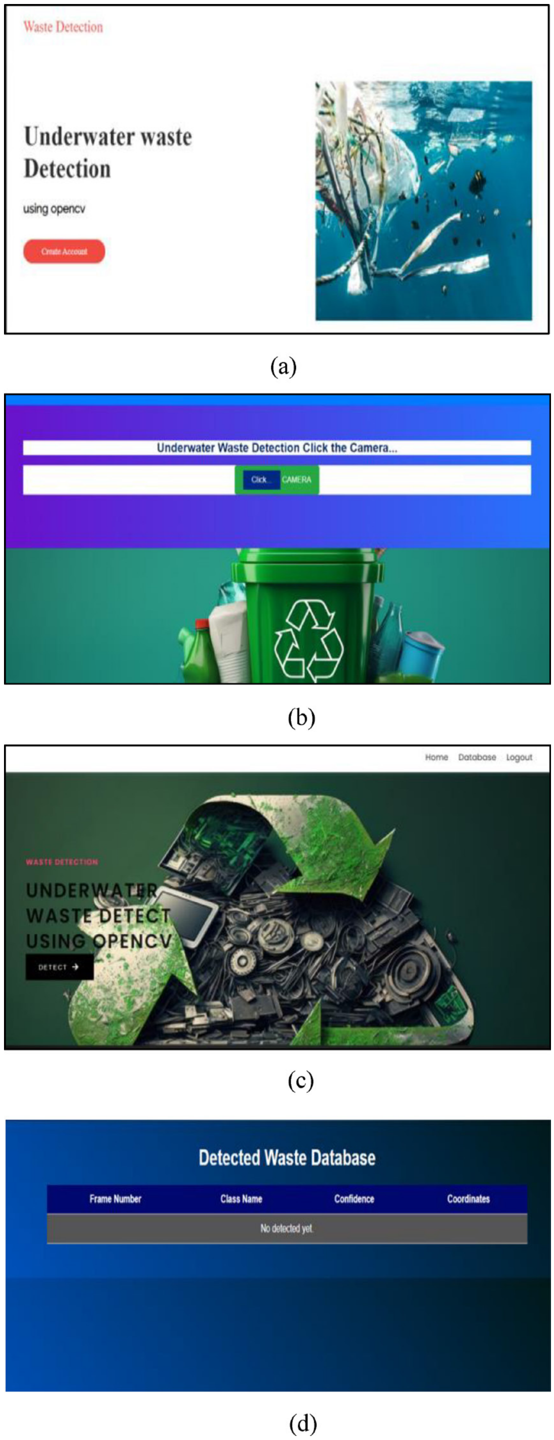


**Fig 2 | (a to d) Website Pages**

and sorting system integrates the YOLOv8 model with Django and OpenCV to create an efficient framework for detecting underwater waste. OpenCV will handle the live feed and image preprocesses; it includes resizing, normalization, and data augmentation. All these improve the quality of the input data to ensure efficient performance by the YOLOv8. The YOLOv8 looks into the images or videos and discovers different types of waste, including plastics, metals, and organic materials. From there it is possible to display the results immediately, raise alerts, or give useful information regarding the type and quantity of waste. Django was used to reveal restful API endpoints for real-time push/pull operations of data. The PostgreSQL database was used to store detection logs and waste category metadata. The backend also managed user autentication, session management, and submission of feedback. Django is a high-level web framework for Python that assists in making the development of secure, reliable, scalable web applications so much easier. This allows developers more freedom to implement meaningful features as most repetitive tasks in building a site have been taken over by it. It is open source, very well documented, and supported by a very vibrant community of developers. This flexibility makes it an excellent choice for this system, enabling the development of a robust web application that allows users to interact with real-time data effectively. The data is around 30% plastics, 25% metal, 15% glass, 30% other rubbish images (like misc, mask, net, etc..). Each class includes more than 500 labeled examples.[5]

Landing page is the front-end user interface that is designed as shown in Figure 2(a) which involves the interface to create an account or register the user to enable access to operate the functions. The camera access page is where the user will be guided to access the camera as shown in Figure 2 (b), where they will be given options of choosing a camera for image or video capture. After capturing data as input the Detection page is opened as shown in Figure 2(c) and the detection process will be initiated then the result will be displayed as a table with values in the Result Database page as shown in Figure 2 (d).

Roboflow makes the detailed workflow related to preparing, using, and applying data sets for computer vision tasks an invaluable tool for developers and data scientists. It begins with uploading your dataset; at this point, users can easily annotate images or import existing annotations in various formats. It makes preprocessing techniques like resizing and cropping, or other data augmentation methods like flip, rotation, or color changes effortless and user-friendly, which are very essential in improving the generalizability of machine learning models. Once you have prepared your dataset, you can create several versions of a design and experiment with several preprocessing, methods and augmentation techniques without altering your original data. This is especially helpful for sorting a few versions of your dataset adapted for different training situations of models. Roboflow can export data sets in compatible formats for multiple machine learning frameworks, including YOLO, TensorFlow, PyTorch, and others, which means exports can be easily utilized for local and cloud-based training, with Roboflow providing sample training scripts to help users initiate the process.[6,7] Roboflow allows hyperparameters like learning rate, batch size, and epochs to be fine-tuned to achieve a better performance in the model. Once trained, the service gives the user all the tools to test their model. Thus, the above metrics like accuracy, precision, recall, and F1-score can be computed to check if the model fits the criteria. In terms of deployment, it offers flexibility through the interference API and supports the use of any cloud-based alternatives for deployment, which would allow the integration of a trained model into a working application promptly. Roboflow encourages further improvement through constant augmentation of the dataset and incorporation of fresh data or feedback to help continuously improve the model. Such an all-rounded approach ensures that computer vision models perform optimally without much resistance.[8]

Figure 2 This web application covers several of the most basic perspectives and functions tailored for specific purposes. The landing page is built using the 1_Landing.html template within the Landing_1 view, which nudges the user to register as a member of the website. The Register_2 view permits users to register by providing them with a registration form, 2_Register.html, after making a GET request. Upon receiving a POST request, the system validates the submitted information, saves the valid entries to the database, and then redirects users to the login page with a success message. The Login_3 view enables users to access their accounts via the 3_Login.html web page. It handles POST requests by retrieving the username and password, and subsequently verifying the user's credentials. Upon successful verification, users are redirected to the home page (4_Home.html); conversely, if there are errors, they are directed back to the login page accompanied by an error message. The Per_Info_8 view oversees the input of personal information, guaranteeing that all details are correctly completed and validated prior to receiving approval.[9] On successful submission of the form, users will be directed to the home page, 4_Home.html; in case the form was not submitted successfully, then the personal info form, 8_Per_Info.html, will appear again. For real-time object detection and classification, the Deploy_9 view will turn on webcam video or photo capture, and use YOLOv8 to detect objects and their classes and record these in an Excel workbook for higher accuracy. These functions help the waste sorting system's database in storing detected models, which include video frame, object type, confidence level, and accuracy, as enumerated in the detected model database. Every view maps to a unique HTML page presented to the users for interaction, where users could feed customized data adjusted to every view's intention.

Algorithm related to Django App:
1. Explain Views:
Landing_1 (User Onboarding Interface)
Unlike a generic landing page, this view is tailored for an aquatic waste detection system, guiding users into a specialized workflow (account creation → camera access → detection results).
The novelty lies in how the page connects users directly to the real-time waste classification pipeline rather than serving as a static page.
Register_2 (Custom Registration Flow)
This view not only handles GET/POST requests for user registration but also links each registered account to detection history and waste classification logs stored in PostgreSQL.
Unlike generic registration in Django, this enables personalized tracking of aquatic waste detection data for each user (helpful in research, analytics, or industry reporting).
Novelty: Integration of user identity with real-time detection results, making the system suitable for scalable monitoring across multiple operators or locations.
Login_3: This page allows a user to log in.
When it receives a POST request: Extracts username and password from the incoming request.
A user can be logged into a Django application via the provided credentials, by calling the authenticate command.
If the user has provided the right credentials: The user will access their account.
To Home page with Address (Home_4) is chosen.
Otherwise: The system will generate an error message.
The system will produce the login page; its number is 3 (3_Login.html)

2. Explain the Submission of Personal Details:
Per Info_8:
When the system has received a POST request: The user personal information must be filled out and validated for accuracy before it can be approved by the system.
The next destination will be the Home page (4_Home.html).
Otherwise: Pages containing details pertaining to personal information (8_Per_Info.html) will be displayed.

3. Object Detection and Classification in real-time:
Deploy_9: When it receives a POST request, Real time means webcam is activated, and takes videos or photos.
Related YOLOv8 which gives class names for detection.
Begin by creating an Excel workbook to hold the results.
Annotated frames shows the previous patterns improving the accuracy to be more than 70%.

4. Database Functions:
Persist the models detected in the set of Detected Model DB with the following fields: Video frame, Type of the object, Level of confidence (Accuracy).

5. User Interface Creation:
For every view created, a corresponding htmpl page is created for the user to fill in the costumized input.[10,11]

**Result and Discussion**

The result for the waste detection and sorting is displayed and the input image of the video after detection will be shown with the confidence level of the detection, the data is stored in the result table as shown in the form of database.[12]

Figure 3: Output showing that the net, plastics, glasses, metals, etc... waste detected with bounding boxes and confidence scores. Visual confirmation demonstrates the reliablity of the trained model. However there are some limitations are exists.[13,14] The detection performance suffers in low-light and turbid


Fig 3 | Input Data Captured and Confidence Percentage

Table 1 | Data Acquistion Table (Database)

| Frame Number | Class Name | Confidence | Coordinates |
|---|---|---|---|
| 1 | net | 81 | (410, 0) to (476, 101) |
| 2 | pbottle | 66 | (514, 3) to (640, 367) |
| 3 | pbag | 94 | (0, 188) to (330, 445) |
| 4 | pbottle | 50 | (487, 0) to (640, 350) |
| 5 | mask | 76 | (464, 3) to (640, 356) |
| 6 | gbottle | 63 | (80, 0) to (284, 303) |
| 7 | tire | 80 | (0, 0) to (116, 362) |
| 8 | tire | 54 | (1, 0) to (247, 470) |
| 9 | pbag | 91 | (2, 0) to (312, 460) |
| 10 | pbag | 81 | (106, 403) to (264, 479) |
| 11 | pbottle | 64 | (162, 404) to (263, 480) |
| 12 | pbottle | 80 | (162, 404) to (262, 480) |
| 13 | pbottle | 85 | (314, 21) to (453, 290) |
| 14 | pbag | 95 | (322, 41) to (450,294) |
| 15 | pbag | 95 | (70, 32) to (80, 44) |

water conditions,with a significant decline in precision.Overlapping or partially occluded objects also results in misclassifications or reduced confidence scores.

Table 1, where the parameters like Frame Number, Class Name, Confidence, Coordinates are stored as shown in Table 1 for efficient data analysis. The Class Name specifies the type of waste object detected, the objects are classified as net, pbottle (plastic bottles), pbag (plastic bag), mask, gbottle (glass bottle), tire, metal, glove, and electronics. The confidence level is the parameter used to determine the accuracy of the system about the object detection as shown in Figure 3. If the detection level is above 50 it is considered to be accurate. The coordinates are used to determine which object is detected in the frame input of multiple objects. It improves multi-detecting efficiency and accuracy. This database can be accessed to improve waste management and sorting of waste efficiently Figure 3.[15] This enhances the system to analyze data regarding the aquatic wastes and the data stored can be used to provide proper handling of aquatic wastes.

## Conclusion

This proposed work achieved automatic separation of waste, with further processing in real-time over video streams, identification of waste objects promptly, and classifies different materials, like plastics, metal, and glass. The real-time detection capability of the system was also subjected to rigorous testing, and this work was proven to operate consistently across various environments while processing video streams without evident delays. Effective implementation in the waste management industry necessitates real-time processing capability since rapid and accurate sorting is needed to enable effective operations. In conclusion, this work satisfies the demand for automation in the sorting of wastes, efficiency is improved, and there are plenty of scopes for improvement and possible future development. One future scope of exploration includes increasing the range of types of waste categorized by the system. In the proposed work, only basic categories of waste like plastics, metals, and glass can be detected by the system.

Future works could focus on optimizing real-time processing capabilities to further reduce latency in aquatic waste sorting management and can improve image quality by deploying better image processing mechanisms to get high-defined images for input from the underwater environment.

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