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# Garbage Monitoring And Management Using Deep Learning

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**Key Words:** Garbage Detection, Image Processing, Vehicle Route Optimisation, Spatial Clustering, Dustbins Mapping, UAV

**Abstract**

Rapid urbanisation and population growth have led to an unprecedented increase in waste generation. In addition to this, increasing tourism has also increased the challenge of maintaining coastal areas. Inefficient and inadequate waste management practices pose significant environmental and health hazards to both humans and wildlife. Through deep learning and computer vision techniques, the garbage can be identified and its location can be extracted directly from the images. Videos are collected using UAVs. Auto generation of waste reports and additional services like chat-bots are also implemented. Furthermore, the system implements OR tools using which the routes of garbage collector vehicles is optimised. By minimising travel distances and maximising cleanup efficiency, the system reduces operational costs and enhances the overall effectiveness of beach cleanup initiatives. Predominant spots of garbage are analysed and the nearest dustbins are mapped along with the route to reach the dustbin. The garbage detection model gave a mAP of 0.845. The silhouette score of clustering was 70.1% for chameleon and 99.02% for k means. All of the above mentioned modules were integrated and presented on the user interface of the application developed.

## 1. Introduction

Coastal regions are facing a huge challenge called shoreline pollution. This pollution interferes and threatens the delicate balance of marine ecosystems as well . Increasing population is also a reason for the increase in waste accumulation in beaches. As an intermediate to land and water, most of the industry waste also gets collected in these regions. Manual effort by the government and environmental agencies is needed to identify these wastes, and there are no provisions to streamline the process of detecting, identifying and collecting the litter. Automation of detection of garbage, and mapping of routes that garbage collectors have to take, can make management of coastal regions easier. This work aims to develop a smart system that can help the required authorities in monitoring the coastal areas, and managing it.

Beaches are pristine natural environments which are very famous for aesthetic appeal. Inadequate waste management practices spoils the appeal and poses hazards to the environment, including human beings and wildlife. Its necessary that these practices be enhanced to become more cost effective and easier. Although there are approaches using deep learning to make detection automatic, a one stop application to provide the analysis, facilities to aid in collection hasn't been developed. More automation and precision is needed while detecting the garbage. Classification of garbage detected is crucial for disposal. This study aims to identify 5 classes - paper, plastic, glass, metal and site. A site is a location which has two or more classes of garbage, or more than one piece of garbage at a point. The other 4 classes are the predominant classes usually found on the beaches. This currently requires in person segregation. Using Deep Learning techniques, this process can be automated which will result in less labour and less effort. As a result, the time taken for classification is also reduced.

Analysing the predominant spots of garbage location with higher garbage accumulation is another important aspect, because beaches are large areas and if there are certain areas that need frequent maintenance, they have to identified. Apart from images, videos can also be segmented into frames to perform the analysis. Integration of GIS and map technologies provide more capabilities to analyse and allocate proximal bins. This will make it easier for the corporation/users to dispose or empty the bin. Computing the areas of the predominant garbage spots would help the corporation to make the necessary arrangements to maintain these spots.

Furthermore, to make the collection process easier and efficient the garbage collector vehicles' routes can be optimised by taking into account the count of garbage at that location and distance to reach that garbage location. To implement this, advanced OR techniques are employed and optimisation is performed. This multifaceted approach aims in providing the collector drivers an easier way to collect garbage by minimising the distance and showing them the route by leading them to the most required spot to be cleaned first, lesser required spot to be cleaned next and so on. This is done by calculating the urgency values. A detailed explanation of the methods used are explained in the following sections.

## 2. Related Works

As urban population continue to grow, effective and efficient disposal and collection of garbage become increasingly challenging. The simplest methodology was proposed by Ritajya Gupta, Dhruv Kumar, Kshitij Jaiswal, Neeraj Vishwakarma (Gupta et al., 2021). Their approach was to use modern day technologies such as Computer Vision, Open CV and some concepts of deep learning (Scarrica et al., 2022) to keep a check on areas which are full of garbage or trash. In order to achieve this goal, they have developed a model using Computer vision and YOLOv5-based Deep neural network (DNN) (V et al., 2022)for garbage detection.

Another article was published in MDPI (Pfeiffer et al., 2022), which used UAVs for beach litter monitoring. It used a

YOLOv5 model for waste detection. Footage from drone surveys conducted on beaches in Malta and Gozo, Sicily, as well as along the Red Sea coast were used. The images obtained from the drone surveys were cut into six square or near-square tiles (two rows, three columns of tiles). Geolocation of the object detections were calculated. Per-class mAP50-95 values, were plotted. Similar to this, Vishal Varma (Verma et al., 2022) proposed a system that uses a quadcopter with an 8 MP camera to capture the images of waste areas. Initially, 2000 images were captured at various time intervals from dusk to dawn and it consisted of images of plastic waste, agricultural waste, biomedical waste, construction waste, household waste, and electronic waste. Two CNN models for solid waste detection using an image dataset captured by the UAV were used and compared (with optimizers - RMSProp and ADAM).The Adam optimizer was found to perform better than the RMSprop optimizer. Inspired by the functioning of unmanned vehicles, a machine to collect and clean debris from canals and rivers was made and presented in by Vyom Rajan Singh, Dr. Chandan Kumar (Singh and Kumar, 2020). The drone was connected with an operator with solid 2.4GHz RF transmitter and receiver system to get more than 1.2km LOS range. All the data from onboard sensors regarding the environment is processed by an Arduino microcontroller and sent over to the operator for driving assistance making the drone semi-autonomous. One of the main features is that, this machine was able to support many more different accessories like GPS, Telemetry, Li-ion battery system etc to improve its functionality and increase user friendliness.

More advancements in garbage detection were made by Li and Tian (Li et al., 2020), by developing a water-surface robot using a modified YOLOv3 network to detect floating garbage with high precision.It was capable of detecting 3 types of waste, move and come back to its initial position.. This approach was evaluated using mAP, and AP, for YOLOv3-3S, YOLOv3-2S with modified anchor boxes, SSD network, Faster R-CNN with visual geometry group backbone, and Faster R-CNN with Res101 backbone. The proposed modified YOLOv3 network achieved 91.43 mAP.

A hybrid approach to calculate zone-to-zone journey times through the use of node-based concepts is proposed by Phillip Soares (Heyken Soares, 2021). The resulting algorithm is applied to an input dataset generated from real-world data, with results showing significant improvements over the existing route network. Nodal approach for route calculation is adapted to work with zonal approach. The time taken to reach the destination and the total time taken to reach the destination are used as optimisation parameters. The hybrid model first calculates the transit times between all node pairs and then identifies the connection offering the shortest overall zone-to-zone journey time for every zone pair.

Another paper by Fadwa Bouhedda and Pilar Garcia (Bouhedda et al., 2021) talks about the SAVs and plastic capture for hotspots analysis in the pacific ocean and its shore. It also concludes that the submerged aquatic vegetation (SAV) zones in and adjacent to MPAs in the San Diego region are potential hotspots for riverine, land-based, and marine plastic waste. This paper concludes that geomorphology of the coast impacts the retention of plastic waste. Bans on plastic bags appear to have reduced the proportion of plastic bags collected in clean-ups in the San Diego area indicating that bans could be a valuable tool to mitigate plastic pollution and the Ocean currents affect the distribution of plastic in the ocean and along coastlines, as evidenced by marine-sourced debris (e.g., fishing gear) found on beaches.

However none of the above discussed paper a full one stop application integrating the analysis and implementation of optimisation. This paper aims in creating a one stop application. Currently, this study leverages crowdsourcing, where any user who uses the application can upload an image containing garbage if they come across it while they are on the beach. The location is extracted. Similarly videos are also split into frames and fed to the model for detection and classification. Along with this, the optimisation and analysis of predominant spots is depicted on maps.

## 3. Materials and Methods

### 3.1 Garbage Detection and Location Extraction

The YOLOv8 model was utilised to detect waste and to classify - glass, plastic, metal, paper, and site debris. This object detection model trains by identifying features like shape, texture, color, size, edges etc. The dataset used was a combination of online, self taken and augmented images. These were annotated using the LabelImg tool. Earlier versions of YOLO were suggested and used by Shalini V (V et al., 2022) and by Rohith Ranjan (Rao et al., 2021) After detection of garbage, metadata (latitude, longitude, time taken) were extracted and the location of the garbage is depicted through a map. The data.yaml file contains the information about the location of training images and validation images directory along with the labelled text files. Batch size and epochs were provided for training the model. Videos were obtained by automated image acquisition techniques using drones/CCTV cameras. Videos were split into frames at specific intervals for video based processing. This is done by identifying the frame rate of the video and saving the frames at certain intervals if,

$$FrameNumber\%Interval = 0, saveimage \tag{1}$$

An interval of 5 seconds was used to generate these frames.

**Data Collection and Preprocessing**. The Dataset contained approximately 600 images altogether from Kaggle, and manual collection. Manual collection consisted of images taken in Beasant Nagar Beach in Chennai. It consisted of images of plastic, glass, paper, and garbage sites. As part of data preprocessing, duplicate image removal, image enhancement through sharpening filters (High pass filters), and augmentation was done. Augmentation resulted in around 1200 images totally.

**Training, Testing and Validation**. Leveraging the YOLOv8 model, the enhanced and annotated images enabled efficient garbage detection. The dataset was split into train and test sets (80% and 20%) and the model was validated.

**Metadata Extraction and Report Generation**. The metadata (features like GPS Coordinates, time taken) of the image uploaded is extracted using exif package in python. An automated report detailing waste information, including quantity, type, location, a map showing the location, and confidence intervals for classified waste, is generated and emailed to the corporation.

Conversion of GPS coordinates from degrees, minutes, seconds system to Decimal System is done by,

$$DecimalDegrees = Degrees + \frac{minutues}{60} + \frac{seconds}{60} \quad (2)$$

$$DecimalDegrees = Integer(Degrees) \quad (3)$$

$$DecimalMinutes = (DecimalDegrees - Degrees) \times 60 \quad (4)$$

$$DecimalSeconds = (DecimalMinutes - Minutes) \times 60 \quad (5)$$

Wikipedia API is a user-friendly Python wrapper providing Wikipedia's API functionalities, enabling extraction of texts, sections, links, categories, and translations. So if waste is detected, information about the class of waste is displayed using this API.

### 3.2 Vehicle Assignments and Route Optimisation

The garbage collecting vehicle needs a route that encompasses all the garbage locations from which it has to collect garbage. Adding a map with live navigation will make it easier for them to collect all garbage. They will also require mapping inside the beach as the current APIs do not provide mapping inside the beaches due to the lack of roads. If the urgency is greater than a certain value, the vehicles are assigned to garbage sites and the optimised route along with the distance is displayed.

**Input Data**. A dataset is created using the results of the previous model containing the latitude, longitude of garbage location, which are extracted from the image and the count of garbage at that location using the YOLOv8 model. Using the dataset of current garbage locations, a vehicle is allocated to garbage locations they have to collect.

**Vehicle Assignment.** The current location of the vehicle collector is obtained using HTML5 API. Given the locations of garbage and the starting location of the collector vehicle, the Euclidean distance between each garbage location and the vehicle collector location is calculated. The urgency is calculated giving equal importance to the distance and the count of garbage, using the below formula:

$$Urgency = CountGarbage + CountSite + \frac{1}{Distance} \quad (6)$$

It takes into account the count of garbage , count of site and is inversely proportional to distance. If urgency is greater than a certain threshold, the location is allocated to that vehicle. The output is displayed on a map and the route from each vehicle to the garbage site is displayed.

**Optimisation.** Once garbage locations and urgency metrics are identified, OR Tools are employed for route optimization. This is performed by routing manager which initialises the number of nodes equivalent to the assigned garbage locations plus one for the starting point. Initial location assignments is done by using the parallel cheapest insertion strategy. Once the optimised route is determined, the Haversine formula is utilised to compute the distance covered by the vehicle in collecting the garbage. Next, the optimised route for the vehicle is visualised using Google Maps API along with live navigation. The output is a map presenting the optimised path to the garbage site assigned and total distance travelled by each vehicle.

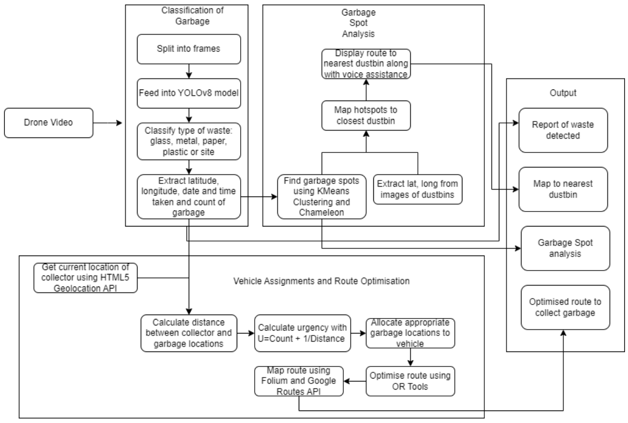


Figure 1. System Architecture.

### 3.3 Spatial Garbage Spot Clustering and Dustbin Mapping

Upon identifying garbage locations, clustering techniques are employed based on spatial distribution and volume to delineate distinct and predominant waste spots . The area of each spot is subsequently computed. To enhance waste management efficiency, the nearest dustbins to these cluster centres are mapped. In addition to this, the routes to the dustbins are shown along with voice assistance to guide the user to reach these bins.

**Input Data.** The dataset used for this module is constructed by including attributes such as waste location, timestamp, date, and waste count (Using images from manual collection - Images of garbages at different locations were taken from the beach at regular weeks (like on a weekly basis)). The metadata that is extracted is added to the dataframe for analysis. The waste count is got by feeding the images to the YOLOv8 trained model.

**Clustering.** KMeans Clustering Method is used to classify using count and Chameleon Clustering to cluster using latitude and longitude. The Elbow method is used for determining ‘K’, the number of clusters for both the clustering methods.The optimal value of k was identified by evaluating the inertia, representing the within-cluster sum of squares, across a range of k values. The inertia values were plotted to determine the point of stabilisation, indicating the optimal cluster number. From the results obtained, the closest dustbins are found and mapped to the spots. In addition to this, the route to the dustbin is also displayed.

**Area Calculation.** Area of the cluster is calculated by defining grid parameters (called cell size). Minimum and maximum of latitudes and longitudes are found.

$$Area = (MaxLat - MinLat) \times (MaxLong - MinLong) \quad (7)$$

Converting Degrees to Square Metres on Earth's surface,

$$AreaInSquareMetres = Area \times 12321000 \quad (8)$$

Based on the area, the corporation can easily assign the cleaning group for cleaning based on the zone where the garbage lies. Route to the hotspots is displayed and a small voice service is made to read out the directions of route.

**Dustbin Mapping.** The nearest dustbins are identified by computing the Euclidean distance between dustbin locations and cluster centres, subsequently visualised on the map for reference. The routes to the dustbins are also displayed.

In order to provide a one stop and user friendly access to all the modules described above, an application should be designed. All the functionalities described above are given a section in the interface. Flask is used for this design. Postgres is used as database at the backend. The detections, maps of optimised routes for vehicles, maps of garbage clustering along with the dustbins mapped, route to dustbins, reports generated, a simple chat bot are all integrated with the application. The admins will receive alerts when there is a new littered site and would then proceed to contact the Corporation so that the required personnel can take the required action. Upon cleaning the site the admin would be able to update the status. The User would be able to upload images when they come across a littered site. The results and above mentioned maps are displayed.

## 4. Results

The YOLO model was trained using a dataset of 1200 images containing all 5 classes. If images were blurred, they were sharpened before annotation and then trained. This sharpening process performed with a high pass filter made the edges more sharper which will be easier to identify features like shape, color, size, texture etc,. by the YOLO model. After training, the model is evaluated using Precision, Recall and Mean Average Precision (mAP).

- Precision implies the accuracy of the detected objects, indicating how many detections were correct - 80.5%
- Recall is the ability of the model to identify all instances of objects in the images - 80.5%.
- mAP is the area under the curve of precision and recall - 84.5%.


Figure 2. Detected garbage

YOLO works by drawing bounding boxes around the objects detected and by showing the confidence levels of each detected class. If an image is uploaded through UI, metadata is extracted. Metadata extracted contains the timestamp, latitude and longitudes. This is done using exif library which gives the GPS coordinates. The report generated is mailed to the corporation.

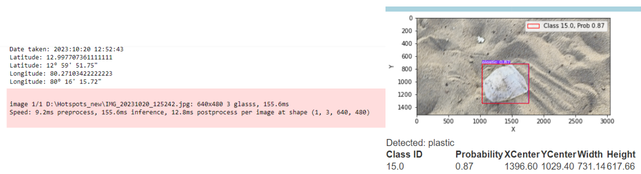


Figure 3. Metadata and report generation

Figure 3 displays these outputs. The information about the generated waste is displayed by wikipedia api and a telegram bot, called the garbot is created - which is used to help the users in navigating the UI by asking questions.

In order to perform the optimisation, once the urgency values of the garbage locations are calculated using the given formula, the vehicles are assigned to the corresponding sites and the routes for these sites are optimised using OR Tools. If the urgency is greater than a certain threshold, it is allocated to the garbage collector. The route the collector has to take is then optimised. This is displayed on the map. The Triangles represent the vehicles and circles represent the garbage. Based on the above factors, the respective vehicle is mapped to the garbage site. The mapped vehicles and garbage are shown below. The blue circles represent the unmapped garbage locations and yellow represent the mapped locations. The routes are also displayed using Google Maps API. The urgency calculated by using the formula is used to assign the vehicles.

```
[3.80378248 3.80382164 3.80295427 3.80429827]
[2.8044077  2.80449247 2.80357676 2.80497025]
[5.802458   5.80256865 5.80162786 5.80304174]
[2.80438918 2.80450657 2.80355946 2.80497772]
[3.80373923 3.80386489 3.80290992 3.8043338 ]
[1.80503397 1.80515419 1.80420344 1.8056271 ]
```

Figure 4. Caluclated urgency values

```
{3: [0, 1, 2, 3, 4], -1: [5]}
[[], [], [], [0, 1, 2, 3, 4]]
```

Figure 5. Assignment of vehicle to sites ( left is vehicle number and right is site number)

The urgency values are ordered in the descending order in a list and the first element corresponds to the highest urgency value. Using the aforementioned method, locations are assigned to the collector vehicles.

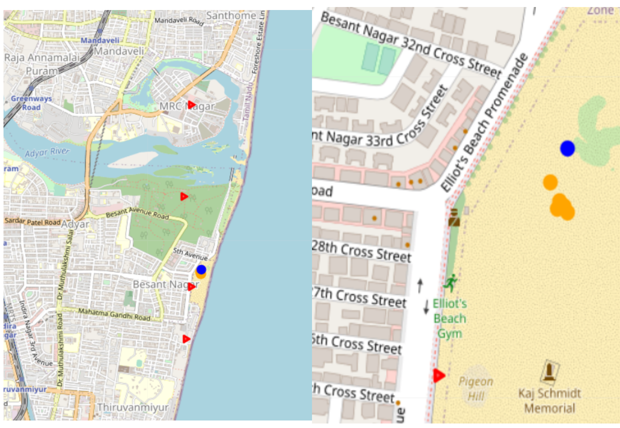


Figure 6. Vehicles mapped

The distance travelled after optimising the route for the vehicles is calculated and shown along with the assigned locations as illustrated in Figure 8. the urgency values and assignments are displayed. Next, the predominant garbage spots are clustered using chameleon(using location coordinates) and KMeans clustering(using count). The K values for each of these were 4 and 8. For this process the extracted information is made into a dataframe as shown in figure 9. The clusters are displayed on the map. The route to the shortest dustbin is displayed. Red circle

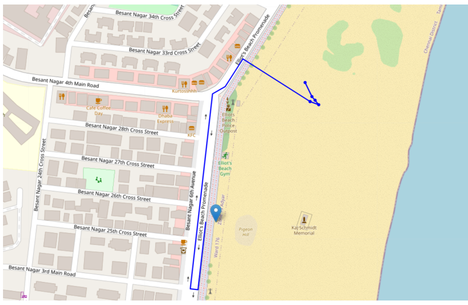

Figure 7. Route for the vehicle to garbage site

```
Vehicle 1 assigned to locations: []
Optimized Route:
Total Distance Traveled for Vehicle 1: 0.00 meters
Vehicle 2 assigned to locations: []
Optimized Route:
Total Distance Traveled for Vehicle 2: 0.00 meters
Vehicle 3 assigned to locations: []
Optimized Route:
Total Distance Traveled for Vehicle 3: 0.00 meters
Vehicle 4 assigned to locations: [1, 2, 3, 4, 5]
Optimized Route:
Location: 5, Latitude: 13.000787722222222, Longitude: 80.27218627777778, Distance to Vehicle: 196.61 meters, Waste Count: 1.0
Location: 4, Latitude: 13.000753388888889, Longitude: 80.27228544444445, Distance to Vehicle: 11.40 meters, Waste Count: 3.0
Location: 3, Latitude: 13.000804888888888, Longitude: 80.27224730555555, Distance to Vehicle: 7.06 meters, Waste Count: 2.0
Location: 2, Latitude: 13.00084686111111, Longitude: 80.27220916666667, Distance to Vehicle: 6.23 meters, Waste Count: 5.0
Location: 1, Latitude: 13.001007055555556, Longitude: 80.27212522222221, Distance to Vehicle: 20.00 meters, Waste Count: 2.0
Total Distance Traveled for Vehicle 4: 241.30 meters
```

Figure 8. Assignment of garbage sites and distance travelled after optimisation

| | latitude | longitude | date | time | count | site | img |
|---|---|---|---|---|---|---|---|
| 0 | 12.997707 | 80.271034 | 2023:10:20 | 12:52:43 | 3 | 1 | D:/Hotspots_new/IMG_20231020_125242.jpg |
| 1 | 12.997722 | 80.271072 | 2023:10:20 | 12:52:53 | 2 | 0 | D:/Hotspots_new/IMG_20231020_125253.jpg |
| 2 | 12.997722 | 80.271057 | 2023:10:20 | 12:52:56 | 1 | 0 | D:/Hotspots_new/IMG_20231020_125256.jpg |
| 3 | 12.997712 | 80.271042 | 2023:10:20 | 12:53:29 | 5 | 1 | D:/Hotspots_new/IMG_20231020_125329.jpg |
| 4 | 12.997668 | 80.271324 | 2023:10:20 | 12:54:17 | 3 | 1 | D:/Hotspots_new/IMG_20231020_125416.jpg |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 147 | 12.998380 | 80.271965 | 2023:10:20 | 13:22:57 | 0 | 1 | D:/Hotspots_new/IMG_20231020_132257.jpg |
| 148 | 12.998355 | 80.271912 | 2023:10:20 | 13:23:11 | 3 | 1 | D:/Hotspots_new/IMG_20231020_132311.jpg |
| 149 | 12.998343 | 80.271896 | 2023:10:20 | 13:23:17 | 2 | 0 | D:/Hotspots_new/IMG_20231020_132317.jpg |
| 150 | 12.998332 | 80.271881 | 2023:10:20 | 13:23:25 | 1 | 0 | D:/Hotspots_new/IMG_20231020_132325.jpg |
| 151 | 12.998413 | 80.271515 | 2023:10:20 | 13:25:07 | 1 | 0 | D:/Hotspots_new/IMG_20231020_132507.jpg |

Figure 9. Extracted information

represents the garbage spot and the green circle represents the nearest dustbin that its mapped to. The area is also calculated based using a grid based method and the approximate measurement of the occupied garbage cluster is done. To enhance ease of usage, the User Interface is equipped with a voice assistance service that reads out the directions that the user has to take to reach the dustbin.

```
Area of Cluster 0: 5.582716049381157e-07 square degrees
68784.64444442524  cm2
Area of Cluster 1: 1.193892340277253e-06 square degrees
147099.47524556034  cm2
Area of Cluster 2: 1.3503086421787783e-08 square degrees
1663.715278028473  cm2
Area of Cluster 3: 1.1111111111552753e-09 square degrees
136.90000000544146  cm2
Area of Cluster 4: 5.339137596431185e-06 square degrees
657835.1432562863  cm2
Area of Cluster 5: 0.0 square degrees
0.0  cm2
```

Figure 10. Areas of clusters

The Chameleon clusters and their dustbins mapped are shown in figure 12. The approximate areas of the clusters are converted to square centimetres and shown in figure 10.

The routes to dustbins are also shown, to calculate the nearest dustbins, euclidean distance metric is used. After clustering base on the count (using Kmeans), the representation was plotted on map. When clicked on each circle, a number of locations

| [114]: | Cluster Number | Dustbins_locs |
|---|---|---|
| 0 | 1 | [12.993478, 80.270509] |
| 1 | 2 | [12.997522, 80.271072] |
| 2 | 3 | [12.993478, 80.270509] |
| 3 | 4 | [12.997522, 80.271072] |

Figure 11. Assignment of dustbins

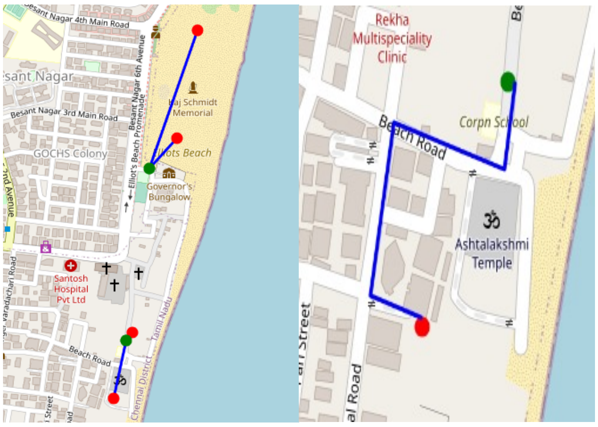


Figure 12. Predominant garbage spots with Dustbins mapped using Chameleon along with the route to dustbin

belonging to that is displayed and on hovering on each of them, the corresponding cluster to which each belongs is labelled.

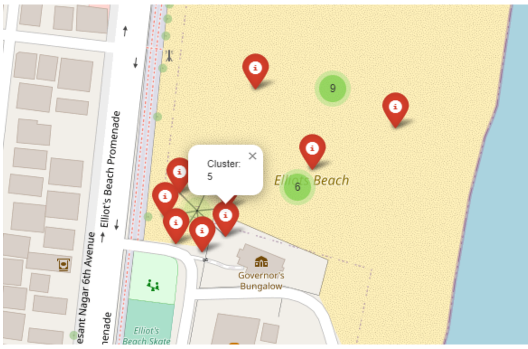


Figure 13. KMeans clustering using count of garbage

To evaluate the performance and effectiveness of clustering three metrics are used: the Silhouette Score, Dunn Index, and Davies-Bouldin Index. The Silhouette Score takes into account both inter-cluster and intra-cluster distance. The garbage locations present within a cluster have to be close to with each other and different clusters have to be well-separated and non uniform shapes should be handled well. Silhouette score takes care of all these. Similarly, the Dunn Index works with irregularly shaped clusters, making it suitable for evaluating the performance of clustering. It is unaffected by the presence of outliers. Lastly, the Davies-Bouldin Index also considers both the compactness within clusters and separation between clusters. Even if the population densities of garbage locations are different in many geographical areas, this index is sensitive to it and can provide a nuanced evaluation.

The UI integrates all of these results and presents it in a user-friendly manner. The status of the garbage, if it's cleaned

| Metrics | Chameleon | Kmeans |
|---|---|---|
| Silhouette Score | 70.106% | 99.02% |
| Dunn Index | 0.883 | 102.73 |
| Davies-Bouldin Index | 0.49 | 0.0038 |

Figure 14. Metrics of Clustering

or not, is also printed. Using this data, the zone where the garbage is present is identified, if the status of the garbage is not cleaned. This Interface is also equipped with a Wikipedia API that provides information about the detected garbage to the user. Further, a telegram bot is created which listens to the user requests and navigates them to the different parts of the User Interface based on their needs.

## 5. Conclusion

This study deals about using innovative technologies like computer vision, operational research (OR) techniques, geographic information systems (GIS) that eases the garbage monitoring process in beaches. Beaches get polluted very often because of increasing human population and their footfall. Traditional methods of shoreline monitoring and garbage detection are often labour-intensive, time-consuming, and costly. By automatically detecting the location of waste from images/videos, optimising and prioritising the garbage collection process, analysing the predominant spots of garbage accumulation and using maps to depict the routes and navigation for users and collector vehicles, the garbage monitoring and management process at beaches is enhanced.

Expanding this system by integrating advanced technologies would be left as part of future work. The images and videos can be obtained periodically like once a week to automate the process of management of litter. Flying drones from time to time would help in faster and cheaper garbage detection and monitoring. In addition to this, garbage monitoring on oceans (marine environments) needs more attention and implementation of collectors to collect the garbage would be a more effective and an easier way to monitor and manage the garbage on the surface of water bodies. Automation of this collecting process without a controller will also have more advantages. Apart from this, the additional real times issues faced by the corporation like monitoring vehicle capacity, garbage bins movement, means of cost effective fuel and disaster management could be solved. All of these future improvements would result in producing more efficient and automatic methods to manage, monitor and collect garbage. In order to achieve these future goals, more real-time data has to be incorporated along with innovations from technology. The impact of the waste pollution can be analysed for both human and wildlife and measures to mitigate must be enforced more strongly.

The solution for more real time issues faced by corporation, optimisations for the server side loads and garbage collection process of using collectors on water marks a significant step towards a more sustainable and technologically advanced solution for coastal cleanup.

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