

Development and Application of an Automatic River-Waste Classification System in Surat Thani and Songkhla, Thailand

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Abstract—This research establishes a Digital Image Processing (DIP)-assisted approach for the identification and classification of primary garbage kinds conveyed by rivers. Various classification models were employed to rectify accuracy deficiencies, and the most proficient model, determined through performance evaluations, was chosen as the basis for an automated trash categorization system. Monitoring stations in Suratthani and Songkhla, prominent metropolitan centers in southern Thailand, were utilized to evaluate the overall quantity of plastic garbage released into the ocean. Classification tasks were performed with Gaussian Support Vector Machine (G-SVM) and Quadratic Support Vector Machine (Q-SVM) models. The findings reveal that the Suratthani River released 1,350 plastic trash items, 720 leaf litter pieces, 130 foam fragments, 233 recognized lipid sheets, and 282 unidentified materials throughout a one-month period during system deployment. In Songkhla Province, 116 plastic fragments and 780 lipid sheets were discovered affixed to unidentified substances. The system is capable of distinguishing lipid sheets, which is a limitation of other classification systems. Additionally, it determines that river waste management should prioritize this type of leakage, as it has the potential to cause the accumulation of small plastics in the river system. These findings highlight the significance of modern digital image processing and machine learning techniques in the surveillance and management of plastic pollution in aquatic environments.

Keywords—ocean, plastic waste, digital image processing, SVM, waste management

I. INTRODUCTION

Marine plastic pollution might reach 10 million metric tons per year by 2050 [1]. Nationwide efforts are underway to track and quantify plastic garbage leaks. Plastic waste's behavior, mobility, and environmental persistence make it difficult to reduce river contamination [2].

Southeast Asian rivers account for 20% of global ocean plastic pollution, although river garbage affects aquatic ecosystems and human health worldwide. The Yangtze, Ganges, and Amazon rivers in China, India, and South America release hundreds of tons of plastic into the oceans each [3]. In addition to plastic trash, metals, fabrics, and chemicals pollute streams and ecosystems. These waste pollutants can travel long distances across river systems, impacting urban and rural regions [4], making management difficult.

River garbage threatens aquatic life worldwide by entangling in plastic debris and spreading poisonous compounds through polluted water. Human health is also affected by river water pollution in drinking, farming, and

fishing areas. Unregulated garbage collection and disposal in rivers in low-income areas worsens plastic contamination health hazards [5].

In Southeast Asia, poor plastic waste management, especially in Thailand, causes river contamination. Nearly 50% of mismanaged plastic garbage in watershed regions in Thailand comes from eleven districts around Bangkok, with 47.6% entering rivers and seas. Beyond Bangkok, southern Thai coastal towns, notably the Thale Sap Songkhla basin, contribute to marine plastic pollution through the Songkhla Lake Outlet. It severely impacts marine ecosystems and biodiversity [6–8].

As plastic pollution rises worldwide, local and international trash management is essential. Southeast Asia is a major contributor to river waste pollution, but all nations must work together to limit garbage flow into rivers and seas. Current efforts to mitigate oceanic plastic pollution rely primarily on measuring and collecting plastic waste from river flows; however, this approach is limited by the waste matrix's complexity, which complicates plastic identification. Integrating Machine Learning (ML) with Digital Image Processing (DIP) offers promising solutions for complex tasks of classification and become one of the solutions for overwhelming this limitation.

The system has been continuously evidenced in classifying plastic types based on specific features and environmental contexts [9–11]. DIP-based technologies demonstrate high accuracy in controlled settings, such as recycling facilities, but are challenged by the diversity and mobility of waste in river systems, these complexities limit the efficacy of such systems in real-world applications because of both sunlight's reflection and complexity of waste matrix.

This study establishes an integration between DIP-supported framework and ML techniques for the detection and onsite-classification of substantial kinds of garbage carried by rivers. The technology has been improved to differentiate garbage from the backdrop and to mitigate the impacts of water movement and reflections. To mitigate accuracy limitations, various classification models were utilized, and the most effective model was chosen as the foundation for an automated trash classification system. This methodology was employed to assess plastic garbage entering the ocean from Suratthani and Songkhla, two prominent cities in southern Thailand.

II. LITERATURE REVIEW

A. Application of Digital Image Processing in Plastic Waste Classification

Digital image processing has been instrumental in advancing the classification of plastic waste. Wahab *et al.* [12] demonstrated a DIP-based automated system for plastic classification with 95% accuracy under standard lighting. Scavino *et al.* [13] used color-based DIP and ML to distinguish recyclable plastic bottles on conveyor systems, while Srigul *et al.* [14] achieved 93.33% accuracy in classifying PET and non-PET bottles using RGB histograms environments.

Agarwal *et al.* [15] introduced a one-shot learning framework for classifying plastic waste based on resin codes. Their model achieved an accuracy of 99.74% on the WaDaBa Database, demonstrating the potential of one-shot learning in waste segregation tasks. Nonetheless, the reliance on a specialized data set raises concerns about the model's applicability to real-world riverine environments with greater variability.

Hanson *et al.* [16] explored the use of snapshot hyperspectral imaging combined with machine learning classifiers to detect macro-plastic litter in river-like scenarios. The method enabled near-real-time tracking of partially submerged plastics. However, the study acknowledged challenges related to the high cost of hyperspectral equipment and the complexity of data processing.

B. Application of Machine Learning in Plastic Waste Classification

The application of Machine Learning (ML) in classifying plastic and river waste has seen significant advancements,

enhancing environmental monitoring and waste management efforts. Van Lieshout *et al.* [17] developed an automated system employing deep learning and camera technology to monitor riverine plastic. Their approach demonstrated the potential of Convolutional Neural Networks (CNNs) in detecting and classifying plastic debris in aquatic environments. However, challenges such as varying lighting conditions, occlusions, and the need for extensive labeled datasets were noted as limitations.

In a similar vein, McShane *et al.* [18] utilized CNNs and TensorFlow to classify plastic waste on river surfaces. Their model achieved high accuracy in controlled settings. Nonetheless, the system's performance diminished when applied to diverse environmental conditions, indicating a limitation in generalizability.

Ahmed *et al.* [19] applied deep learning to industrial plastic recycling, achieving an accuracy of 0.79%, with success (90%) on colored plastics.

Majchrowska *et al.* [20] utilized neural networks layered with DIP for household waste plastic classification, and Van Lieshout *et al.* [17] implemented an automated monitoring system using R-CNN segmentation to detect and quantify floating macro plastics in Indonesian rivers, indicating robust system potential with an R^2 value of 0.43.

The integration between Digital Image Processing (DIP) with Machine Learning (ML), are commonly applied in association with each other in handling the classification of plastics. It offers promising solutions for complex tasks, such as classifying plastic types based on specific features and environmental contexts. Even supposing that this integration scheme can perform high accuracy in the classification, thus the system still confronts the limitation as mentioned in Table 1.

Table 1. Summarization of the limitations of current integrated DIP and ML for transported plastics in riverine for monitoring system

Study	System/Methodology	Limitations
Wahab <i>et al.</i> [12]	DIP-based automated system for plastic classification with 95% accuracy under standard lighting	Performance depends on standard lighting conditions; may not be robust in varying lighting environments.
Scavino <i>et al.</i> [13]	Color-based DIP and ML system to classify recyclable plastic bottles on conveyor systems	Limited to conveyor systems and relies heavily on the color properties of plastic.
Srigul <i>et al.</i> [14]	RGB histograms for classifying PET and non-PET bottles, achieving 93.33% accuracy	Limited accuracy and applicability when the plastic waste is contaminated or not in predefined forms.
Agarwal <i>et al.</i> [15]	One-shot learning framework with Siamese and Triplet loss CNNs	Reliance on a specialized dataset (WaDaBa Database) limits generalizability to real-world conditions.
Hanson <i>et al.</i> [16]	Snapshot hyperspectral imaging combined with ML classifiers	High cost of hyperspectral equipment and complexity of data processing.
van Lieshout <i>et al.</i> [17]	Automated monitoring system using R-CNN segmentation for detecting floating macro plastics in rivers	Low R^2 value (0.43) indicates limitations in accurately quantifying floating macro plastics.
McShane <i>et al.</i> [18]	CNNs and TensorFlow for classifying plastic waste on river surfaces	Performance diminishes in diverse environmental conditions, limiting generalizability.
Ahmed <i>et al.</i> [19]	Deep learning for industrial plastic recycling, achieving 0.79% accuracy and 90% success on colored plastics	Low overall accuracy (0.79%) indicates limited system performance for uncolored or mixed plastics.
Majchrowska <i>et al.</i> [20]	Neural networks layered with DIP for household waste plastic classification	Limited robustness for complex, mixed, or contaminated household waste.

The prevalent constraints in these investigations mostly pertain to environmental reliance and system generalizability. Recent studies have improved plastic classification systems through various methodologies; however, many are constrained by environmental and operational factors. DIP-based methods demonstrate high accuracy in controlled environments; however, their performance declines under varying lighting conditions or outside conveyor setups. RGB histogram methods faced challenges related to contamination

and non-standard waste forms. Moreover, advanced imaging techniques exhibit potential yet encounter challenges related to cost and complexity. Deep learning methods for recycling and waste monitoring demonstrate potential; however, they necessitate wider applicability. The integration of preprocessing methods to address contaminants, in conjunction with transfer learning and data augmentation techniques, may enhance system accuracy and resilience. Ongoing innovation in these domains is essential for the

effective scaling of these technologies to practical applications.

In order to diminish these obstacle as well as increasing the capability in segmentation and classification of waste, the system employed in this study has been constructed by using layers of analysis for separate the complex of the waste and can significantly achieve the expectation.

III. MATERIALS AND METHODS

The framework of this research is succinctly captured in Fig. 1. An investigation of the site was conducted to ascertain the properties of waste that was conveyed through the open channel linked to the estuary of the research site. Mounted on bridges across the channel, high-resolution CCTV cameras comprised the real-time monitoring system, which collected and transmitted continuous data to an algorithm designed to classify waste based on the monitored categories. Subsequently, the classification outcomes were corroborated using actual observation data. An empirical DIP calculation was used to get a better idea of how much of the identified main waste leaked into the oceanic system.

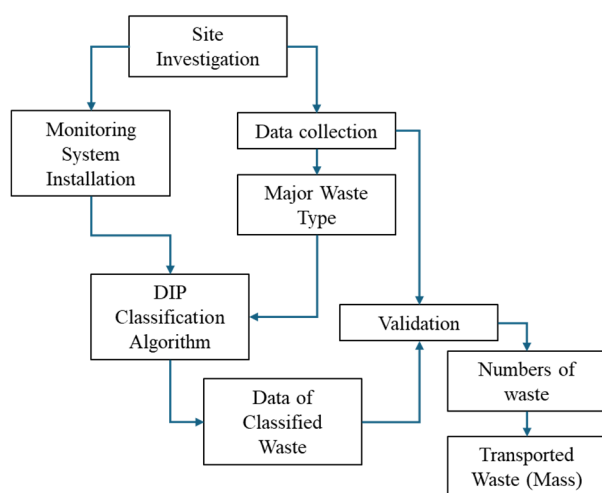


Fig. 1. Summarized framework of this study.

A. Site Description and Field Observation

The project aimed to monitor complex waste categorization in dynamic environments. Therefore, two significant cities in the southern parts of Thailand were selected as the study locations. The primary training location is in Banglhar village, Suratthani, Thailand. The given coordinates represent the position in UTM format, specifically in UTM zone 47N, with easting of 535156.67 and northing of 1011508.38. This website showcases the significance of the association with the Tapi River, which serves as the main river immediately connected to the Gulf of Thailand. The waterway passes through residential areas where fishing and its associated products serve as the primary source of revenue. Furthermore, the second location is near the estuary of the Kaoseng Canal in Songkhla, Thailand. The geographical coordinates are UTM 47N 678683.47 E 794082.41N. The canal is directly connected to the Thale Sap Songkhla Lake and its estuary. Fig. 2 illustrates the canal's path as it passes through various municipal regions, including villages, markets, and a mosque. Field observations in this study were carried out by both human observers and

monitoring systems. The direct field observation was carried out from January of 2022 at both locations. The garbage transportation over the waterways of these sites was monitored and documented by human observers.

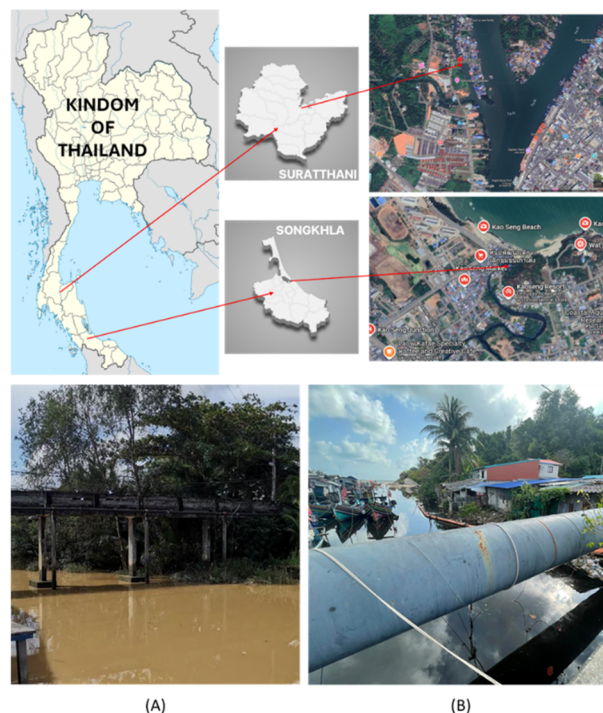


Fig. 2. The location of monitoring stations in this study (A) Banglhar village, Suratthani, Thailand Summarized framework of this study (B) of Kaoseng Canal, Songkhla, Thailand.

B. Monitoring System

The remote system comprised an IP camera and a data transfer module utilizing Wi-Fi communication. Every camera is immediately linked to the router to transfer the video footage to the cloud. Subsequently, the videos are transferred to the external hard drive as a precautionary measure to avoid exceeding the storage capacity of the cloud. The cameras were arranged at a right angle to the sea surface. To achieve precise garbage classification, a number of advanced IP cameras with high-resolution capabilities have been installed to provide comprehensive coverage of the entire waterway. Table 2 provides a comprehensive summary of the camera specs and the availability of data. The camera recorded continuous videos of transported waste at each designated place. The videos were captured at a 1080p resolution and had high compression capability to minimize the impact of natural light conditions [18, 19]. These specification can support the enhancement of data when the combination of DIP and CL performing the transformation of the videos into the sets of photo for clustering and analysis.

Table 2. Required Specification of camera, using as sensor for waste detection

Camera	
Image Sensor:	1/3" Progressive Scan CMOS
Video bit rate:	32Kbps~16Mbps
Resolution:	2688×1520
Framerate	60Hz: 20fps (2688×1520), 30fps (1920×1080), 30fps (1280×720)
IR Range:	I3: 30m; I5: 50m; I8: 80m

C. Classification-Model Development

The model architecture is structured hierarchically. Every individual node in the process tree represents a node, which is part of the classification model used for image segmentation and waste type classification. Fig. 3 displays the configuration of the model, while Fig. 4 demonstrates the detail in classification of each model.

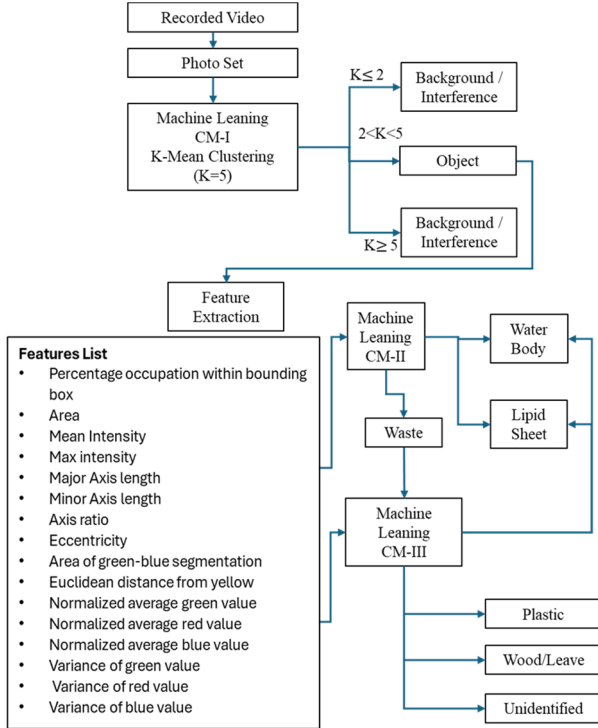


Fig. 3. Model architecture for waste classification in this study.

The Classification Module I (CM-I) employs the cubic support vector machine, a highly effective instrument, to distinctly differentiate between water bodies and waste in background and object separation. The ten features comprise area, pixel count in the convex area, major axis length, minor axis length, mean values of the red, green, and blue channels, and the variances of the red, green, and blue channels. Classification Module II employs these features in the same manner. The secondary model utilizes these attributes to differentiate between water bodies and waste with greater precision. Ultimately, CM-III's principal algorithm for waste classification employs image segmentation through k-means clustering. Three modules are integrated to develop the system's automated classification program in machine learning. Data-driven learning enhances machine learning. The majority of machine learning algorithms employ optimization techniques, whereas others utilize parameter regulations. In order to investigate the impact of waste transportation in natural waterways, the study collected high-performance recorded videos (1080p video stream with H.264+ compression) from monitoring stations over a period of three months (January-March 2022). The training dataset for classification and computation in this work consists of 16,678 segmented sections from the video, as specified by the previously established architecture.

D. Estimation of Transported Plastic Waste

The quantification of plastic garbage in the canal has been carried out using the recorded quantity of waste that may be

observed and categorized by the monitoring system. Fig. 4 illustrates the algorithm used to estimate the amount of released trash in the water phase. The identified garbage was subsequently quantified to determine the quantity of each categorized kind, using the unit weight (or average weight obtained from direct field observation) for calculation. The calculating technique will yield the weight of water leakage per monitoring boundary per unit of time. These values will then be aggregated to determine the total number of waste-leakages in the water phase from the municipality at a later stage.

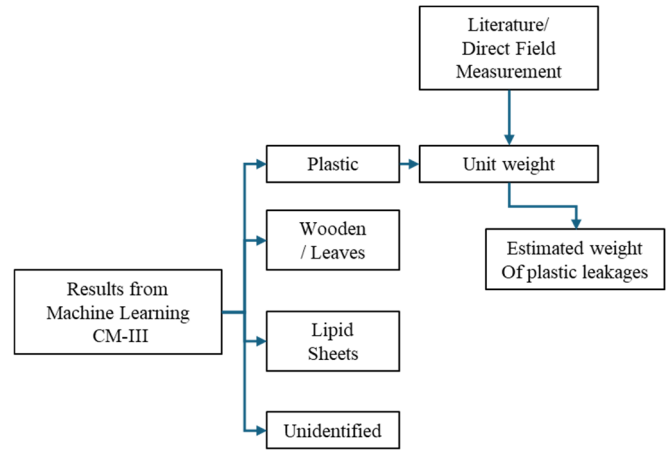


Fig. 4. The estimation algorithm for leakage in water fate.

The algorithm for estimating each waste type can be estimated, according to Eq. (1). The unit weight per area (A) of the waste is represented as w , while the area of the waste, recorded from the camera, is determined as

$$A_c W_u = wA \quad (1)$$

In this study, the area of the waste can be obtained by the summation of area from the integration of pixels in the boundary of the waste as presented in the calculation formula in Eq. (2), where a_c refers to the area of each pixels in the waste and n refers to the countable pixels within the waste's boundary.

$$A_c = \sum a_c \quad (2)$$

Since the area of each pixel can be calculated using n the smallest fraction in resolution of the video recording device so the area of each pixel can be determined as Eq. (3), where FOV stands for the field of view of the camera and R refers to the resolution of the camera. According to these relationships the formula for calculating of weight for each waste body from the camera can be estimated using Eq. (4)

$$a_c = \left(\frac{FOV}{R}\right)^2 \quad (3)$$

$$W_u = w \sum \left(\frac{FOV}{R}\right)^2 \quad (4)$$

To determine the total amount of transported wasted from the water system in in the monitoring area the ratio between detected plastic (n) and the Area of Interest (AOI) of the system are use as requisite factors in the estimation. Eq. (5) represents the calculation scheme for the total transport wastes where T refers to the total transported waste and A_w is the representative of the total area of the monitoring

channel, therefore the total weight of transported plastic waste (T) can be estimated based on Eq. (6) where E stands for the accuracy of the system in classification.

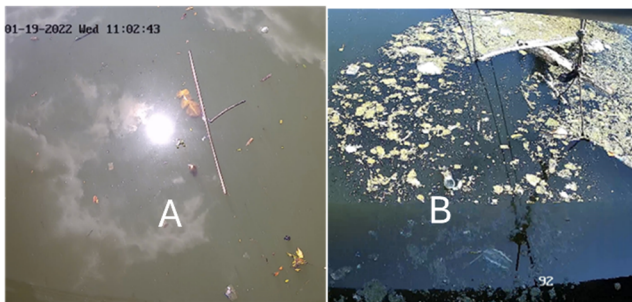
$$d = \left(\frac{W_u}{AOI} \right) \quad (5)$$

$$T = EdA_w \quad (6)$$

IV. RESULT AND DISCUSSION

A. Data Observation and Validation

The primary data collected from the monitoring system during January-February 2022 reveals notable differences in the characteristics of the transported waste across the waterway from the study sites. In Suratthani, there is a higher flow rate of water, with a significant presence of plastics, wood, and mixed debris that are difficult to classify. In contrast, lipid sheets and organic debris are the predominant contributors observed in Songkhla province. The collected observation data and identified wastes from the monitoring system undergo a thorough manual examination to confirm the type of wastes prior to their utilization as input for the classification model. The primary categories of waste identified throughout the monitoring period are presented in Fig. 5. The unclassified debris consists of waste materials that are interconnected, including Java weed and floating fishnet.



Type of Waste	Detected and validated Waste			
	Suratthani		Songkhla	
	Pieces	%	Pieces	%
Plastic	1,517	46.00	135	6.49
Wooden/Leaves	888	26.94	67	3.23
Lipid Sheets	159	4.82	4	0.17
Unclassified	733	22.24	2,700	92.9
Total	3,397	100	2,906	100

Fig. 5. Primary categories of waste in the study area (A) Suratthani province (B) Songkhla province.

B. Model Development and Evaluation

The CM-I employs k-means clustering for image processing [21]. The parameter “k” denotes the number of clusters designated for the k-means clustering algorithm. When k equals five, the process of categorizing each pixel in an image into five clusters necessitates the identification of mean values that minimize cluster variance. Fig. 8 illustrates the application of the k-means clustering algorithm with k set to 5. The algorithm can differentiate between the scattered light layer of water and the shadow cast by a tree. Both the regions of light reflection and tree shadows contain objects.

The area of the object will consist of central clusters, where the highest cluster indicates the sun’s illumination and the lowest represents the tree’s silhouette. The image undergoes

binarization based on established rules. Following binarization, the binary image is subjected to morphological operations such as closure, opening, and dilation to facilitate object detection. Fig. 6 presents the results of object detection. The illustration demonstrates that light reflection and shadow do not obscure the objects. Bubbles and leaves are, regrettably, present. The CM-I procedure effectively removes false positives.

The classification models are initially applied to the 24-h Suratthani dataset video to minimize false positives. Video images are processed at 5-min intervals. The model validation process employs 16,678 k-means-based video segmented regions. There are 15,109 segments in the background regions. The area of interest comprises 6% of the data, encompassing 1,169 segmented complex debris object areas.

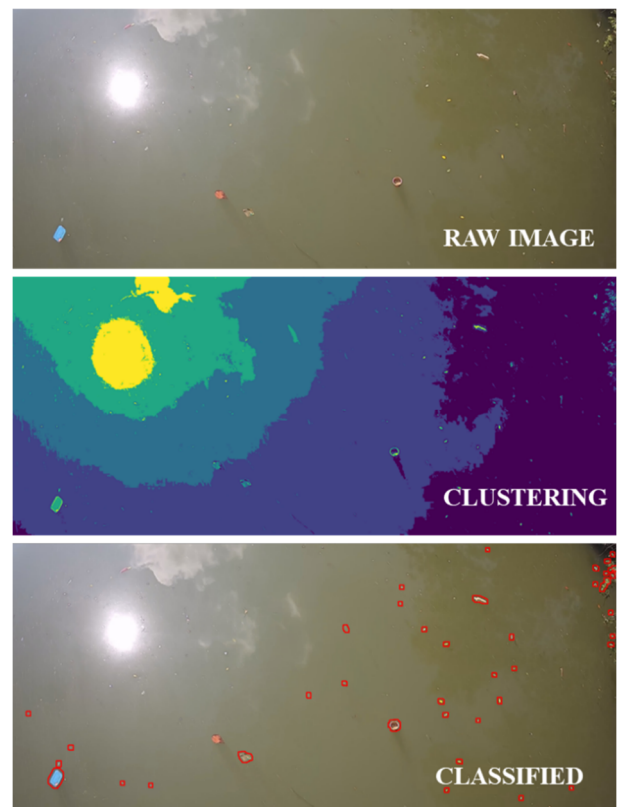


Fig. 6. The classification results of transported waste.

According to Sutatthani dataset, the accuracy of the models is indicative of the quality of the extracted image features as mentioned in Table 3. Skewed data diminishes the accuracy of object detection models. This example illustrates the precision and recall metrics utilized to elucidate the model. According to the results, the Quadratic Support Vector Machine (Q-SVM) was selected for background elimination because of its enhanced performance. The quadratic SVM achieves a recall rate of 73.7% for identified objects. The recall percentage, or True Positive Rate (TPR), represents the proportion of data samples that a machine learning model accurately identifies as belonging to a specific class, relative to the total number of samples within that class. The quadratic support vector machine serves as the primary training algorithm. In CM II, the background dataset of this model will be reclassified for the purpose of object detection. More than 90% of the objects have been identified and are proceeding to CM III for classification by waste type.

Table 3. The results of 5-fold cross-validation for the background elimination task from Suratthani's data set

Classifier	Accuracy (%)	Precision (%)	Recall (%)
Tree classifier	97.0	79.3	67.7
Quadratic discrimination analysis	93.5	52.8	72.0
Linear discriminant analysis	94.8	61.0	70.4
Linear SVM	96.1	78.0	61.5
Quadratic SVM	97.2	84.7	73.7
Gaussian SVM	90.4	82.8	70.1
K-nearest neighbor	97.0	82.4	72.0
Bagged tree classification	97.0	84.7	72.5
Subspace K-NN	94.7	80.6	63.1
Average	95.3±2.1	76.2±10.7	69.2±4.0

For the Songkhla dataset, the density of waste in input images is more than the Suratthani dataset. In the Songkhla dataset, there are 5,162 segmented images for model validation. The segmented images include 3,149 segmented backgrounds, the portion of the background is 61% in the dataset. Then, the segments of the lipid sheet occupy 37% of the dataset and the other 3% are plastic and wood. The models' performance for the background separation task is shown in Table 4. The best performance is also provided by the Quadratic SVM. According to the model, 87.7% of objects are detected by the model while 80.8% of background

segments are separated.

After the background elimination of the data from this station, the classified object areas consist of 4 type of object including plastic, wooden, lipid/organic debris and unclassified debris. According to the examination the lipid/organic debris overwhelms other types of object in terms of both eyesight and primary -computed classification, therefore it has been chosen to be the first group for trash type classification. The cross-validation test is again applied to the dataset as shown in Table 5 and the best accuracy is provided by the Gaussian SVM model, so this model is used for CM-II and CM-III classification for Kaoseng canal.

Table 4. The results of 5-fold cross-validation for the background elimination task for Songkhla dataset

Classifier	Accuracy (%)	Precision (%)	Recall (%)
Tree classifier	84.8	81.5	83.3
Quadratic discriminant analysis	74.9	82.5	56.7
Linear discriminant analysis	83.4	79.2	86.1
Linear SVM	83.3	79.1	86.1
Quadratic SVM	86.2	80.8	87.7
Gaussian SVM	82.8	82.4	88.4
K-nearest neighbor	85.6	83.2	85.5
Bagged tree classification	85.9	84.2	84.8
Subspace K-NN	80.0	77.2	79.4
Average	83.0±3.4	81.1±2.1	82.0±9.2

Table 5. Result of cross-validation test, based on the data from Kaoseng Station

Classifier Model/Module	Accuracy (%)			
	CM-I		CM-II	CM-III
	With lipid sheet	Without lipid sheet		
Tree Classifier	97.0 ± 2.4	86.5± 2.5	94.1 ±0.2	97.6 ±0.1
Quadratic discriminant	93.5 ± 3.2	unable to classify	94.2 ±0.7	unable to classify
Linear Discriminant Analysis	94.8 ±2.1	87.9±5.4	94.3 ±0.8	96.1 ± 0.3
Linear SVM	96.1 ± 2.2	87.8±2.4	94.6 ±1.2	97.6 ± 0.5
Quadratic SVM	97.2 ± 1.3	89± 0.2	95.3 ±0.1	97.7 ± 0.1
Gaussian SVM	90.4 ±1.4	88.1±1.0	95.6 ±0.6	97.6 ±6.6
K-nearest neighbor (K-NN)	97.0 ± 1.7	87.1±2.0	95.2 ±0.5	97.6 ±1.7
Bagged tree classification	97.0 ± 2.3	87.8±1.6	94.1 ±0.4	97.7 ± 0.6
Subspace K-NN	94.7 ± 5.4	unable to classify	93.1 ±1.9	unable to classify

As a consequence of the efficacy of background elimination on both datasets, the model is capable of delivering enhanced mean recall and precision. The low scores in the Suratthani datasets are attributable to the bias introduced by the dataset's background segments. In situations where the quantity of background segments exceeds the quantity of object segments, the optimization procedure may induce the model decision rules or function to detect additional background in order to achieve a higher score. Therefore, the mean recall score is exceedingly low within this dataset. Nevertheless, an alternative model functions as a secondary filter, retrieving the misclassified objects and reintroducing them into the system for the purpose of object identification or classification. The subsequent sub-topics detail the efficacy of the object identification and classification processes.

C. Model Development and Evaluation Estimated Transported Waste

The outcomes of an analysis of refuse segregation using the developed system. The study's findings are depicted in

Fig. 7. It was discovered that the waterway of Suratthani discharged 1,350 pieces of plastic refuse, 720 pieces of leaf litter, 130 pieces of foams, 233 detected lipid sheets and 282 objects of unspecified type over the course of one month for data collection and system installation. Furthermore, the leaked in the study area of Songkhla Province comprises 116 plastic pieces. Although no leaf fragments were identified, a total of 780 lipid sheets bidding with undefinable material at 1,132 pieces were discovered.

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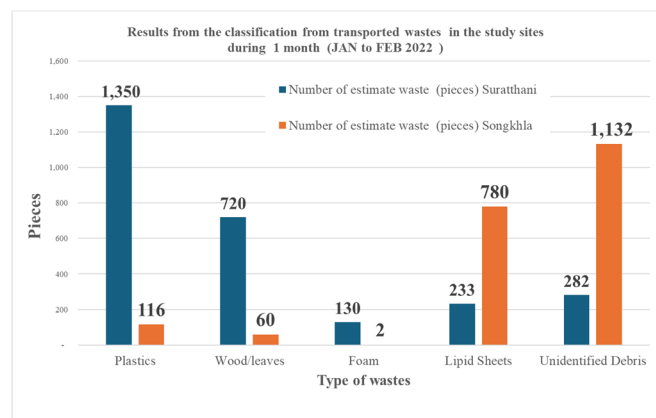


Fig. 7. Numbers of waste, transported in the river system of the study area during the monitoring period (Jan. 2022-Feb. 2022).

The FOV factor can be determined using both calculation and direct field measurement as demonstrated in Table 6. The study involved calibrating the apparent resolution at the monitoring point using a 60×85 mm polypropylene cardboard. The cardboard was securely fastened to the rope, positioned 5 m from the CCTV camera, to determine the Field of View (FOV) of the monitoring station. Based on the experiment, the Field of View (FOV) for all the installed cameras in this study is computed at 0.2055 pixel/m². In this study the average unit weight of plastic is assigned at 0.00179 g/mm² according to the study of [22].

Based on the estimated findings, there are variations in the amounts of plastics moved through the channel at both monitoring sites, and the number of plastics transported is linked to the size of the channels. The plastic transportation weight over the Suratthani's station is estimated to be 18.42 kg. Given that the monitoring equipment is currently installed at only one of the branches, which covers a mere 5% of the estuary's entire area, the cumulative amount of plastic transported during the monitoring period may exceed as much as 386.40 kg. Considering that the monitoring of Songkhla province can encompass a larger portion of the outlet region compared to Suratthani, it is observed that the channel is polluted and coated with lipid sheets, leading to the reduction of accuracy, and detected quantities of plastics. Although the total amount of transported plastic waste from this station cannot be accurately specified, thus the total detected plastic from the station can be defined at 43.48 kg/month.

Table 6. Estimation factors and results of transported plastic over the water way from the monitoring sites

Parameter	Study site	
	Suratthani	Songkhla
FOV (pixel/ m ²)	0.2055	
Average Weight (g/mm ²)	0.00179	
Chanel area (m ²)	104	296
Area of Interest (m ²)	20	
System Accuracy (%)	95.3	81.4
Total Pixel of detected plastic waste (cell)	427,517	106,115
Area density (g/m ² /m)	0.0697	0.0346
Estimated Total weight of transported Plastic (kg)	18.42	43.84

D. Discussions and Suggestions

Despite the fact that the achievement of the waste classification from municipal areas are hardly managed, thus the results from the monitoring system demonstrate that the system can enhance their monitoring and collection. By the capability of the system that can account wastes numbers, the estimation of waste quantity based on time can be accomplished.

The CM-I procedure involves applying a set of criteria to filter out false positive detections. This process ensures that only the desired objects are accurately identified, and any unwanted particles are removed from the result. Additionally, the CM-I procedure helps to enhance the overall accuracy and reliability of the object detection process. With Quadratic SVM, the system also achieves a high accuracy of 93.2% in correctly classifying the segmented lipid sheet. Additionally, the model successfully separates plastic and wood segments with an accuracy of 85.6%.

Even supposing that the system can effectively classify each significant type of waste with high accuracy from the developed algorithm. Thus, the lipid sheets and floating rucks can reduce the performance of the system. At the monitoring site of Songkhla province, the portion of detected lipid sheets is higher than in Suratthani, resulting in the decrease of the system's accuracy. According to the findings, the improvement of clustering methods can be one of the key to improving the system's performance. K-mean clustering with extensive classes have potential in designation of differences in the color of heterogeneous compositions, including lipid, plastics and foam. Moreover, assembling specific sensors such as hyperspectral cameras can be benefits to the systems' performance. The hyperspectral camera can capture the picture and classified the objects by determining the individual reflectance of each material.

Based on the findings of the investigation, The characteristics of the river and waterway can have varied impacts on the type and quantity of waste that enters the sea. The research conducted in the Bang La Subdistrict of Suratthani Province revealed that natural waterways, which receive significant volumes of waste from the tributaries of the river, serve as a prime illustration of the challenges associated with managing such water systems. The reason for this is its substantial size and its ability to amass the highest quantity of waste within a given timeframe. However, in the specific region of Kaoseng Subdistrict, close to densely populated neighborhoods and families exhibited a greater quantity of 2,088 identified and unidentified substances. This is due to the presence of interconnected debris rafts, held together by a layer of accumulated lipids.

Hydrological processes, such as tides and water circulation, can influence the quantity of debris that seeps into the ocean. The research site in Bang La Subdistrict, Suratthani Province, connected to both the Tapi River and the Gulf of Thailand contains a greater level of leakage compared to other regions. This pertains to the impact of water flow rates in expansive rivers. Hence, to effectively minimize waste leakage, it is crucial to identify and concentrate waste flow in the tributary regions. Beyond the act of gathering refuse in the estuary, the execution of this collection can be facilitated with the collaboration of local administrative entities.

The system demonstrates exceptional abilities in segmenting and classifying intricate matrices of river waste, positioning it as an essential resource for local authorities aiming to mitigate the risk of municipal waste contaminating adjacent oceans. Through additional refinement, the system has the potential to integrate real-time weight estimation of retained waste, evolving it into an automated collection mechanism. Through the quantification of the overall mass of waste collected in sieves linked to water gates, the system has the potential to enhance the efficiency of waste removal operations. These advancements could transform waste management in tributaries that feed into major rivers, facilitating a synchronized and effective approach to waste flows on a continental level.

Hyperspectral imaging (HSI) has proven to be a valuable technique for detecting and classifying plastic waste in riverine environments and can become the enhancement-integration of this system. To enhance its accuracy, the system could incorporate hyperspectral sensors that can distinguish waste types based on their distinct wavelength responses. This enhancement would greatly elevate classification accuracy. Nonetheless, guaranteeing that these sensors can endure severe weather conditions continues to be a significant obstacle for sustained deployment and efficacy. The integration of HSI with sophisticated computational techniques offers a comprehensive examination of plastic pollutants, enhancing monitoring effectiveness in aquatic ecosystems [22].

The worldwide application of HSI for detecting plastics in river systems offers significant possibilities for the future. Technological advancements are expected to reduce equipment costs and improve data processing efficiency, thus making HSI more accessible for environmental monitoring applications. The implementation of standardized protocols and the fostering of interdisciplinary collaboration have the potential to enhance the effectiveness of HSI applications. Confronting these challenges could position HSI as a crucial tool in global initiatives aimed at monitoring and mitigating plastic pollution in aquatic ecosystems [23].

Furthermore, advanced remote sensing technology, driven by satellite imagery, presents a transformative solution in addressing oceanic plastic leakage. The MAP-Mapper, alongside the Marine Debris Map (MDM), has shown remarkable accuracy, pinpointing waste materials with a precision rate of 95% and a recall range of 87-88%. This technology facilitates the monitoring of plastic waste movement across continents and allows for the categorization of various waste types, positioning it as a crucial element in worldwide waste management initiatives.

Recent advancements, including hyperspectral remote sensing and the use of Unmanned Aerial Vehicles (UAVs), have significantly improved the monitoring of plastic debris in coastal areas and estuaries. Nonetheless, the ongoing problem of undersea leakage continues to pose a significant challenge. Addressing this challenge will necessitate creative approaches to guarantee the long-term health of marine ecosystems globally [24–27].

Even if the system can be developed and still has numerous opportunities for improvement into a precise monitoring system, it cannot reduce the leakages of waste, particularly plastics, into the oceanic phases. The implementation of the

system from these study sites indicates that the surrounding community along the bank plays a crucial role in mitigating this contamination. The investigation into the connection between income knowledge and cultures requires further exploration to identify optimal practices for minimizing leakage, which will serve as a crucial mechanism for supporting the sustainability of river and oceanic systems.

V. CONCLUSION

This study develops and implements an automated river-waste sorting system in Suratthani and Songkhla, Thailand. River trash is identified and classified using Digital Image Processing (DIP) in association with Machine Learning (ML) techniques. The Quadratic Support Vector Machine (Q-SVM) proved to be the most appropriate segmentation and classification with up to $97\pm0.1\%$ accuracy and has been chosen to be the main algorithm for background reduction detection training. The developed system was applied in both study sites for examining the waste, transported through the water channels. According to the results it can be seen that the system contains high capability in distinguishing the extremely complex waste-matrix and the background in the real situation. The data collection and system installation were conducted during January to February of 2022, detecting 18.42 kg and 43.84 kg of plastic waste that were transported in Suratthani and Songkhla respectively.

The significant amount of garbage in natural rivers especially plastics, binding with lipid sheets makes water system management difficult, the developed system remarkably detected the existence of them, making the system a vital resource for local agencies in their future's waste management. It can be enhanced into real-time weight assessment of retained garbage which might improve waste removal efficiency, while the hyperspectral sensors, attached and integrated to this current system might improve classification accuracy by matching the anomaly that the specific waste responses to the variants of the wavelengths, thus their endurance for the extreme condition such as heavy rainfall and high atmospheric temperature still become concerns. While the development of a precise monitoring system offers potential for improvement, it cannot fully prevent plastic waste from leaking into the oceans. The involvement of local communities along riverbanks is critical in addressing this contamination. Further research into the relationship between income, knowledge, and cultural practices is essential to identify effective strategies for reducing plastic leakage and supporting the sustainability of river and ocean ecosystems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Somprasong S., conduct the research idea and write the manuscript. Mongkholchai A., revises the manuscript and contributes the suggestion for the management of the area. Manorot P., conducts and evaluates the DIP and investigates the performance of the system. All authors had approved the final version.

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