IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, November 2023

Efficient Classification of Marine Debris using SVM with Noise Removal and Feature Extraction Techniques with Improved Performances

S. Belina V. J. Sara[1,2] and A. Jayanthila Devi[3]

PDF Research Scholar, Srinivas University Mangaluru, Karnataka, India[1]

Assistant Professor, Department of Computer Applications, SRMIST, Kattankulathur, Tamilnadu, India[2]

Professor, Institute of Computer Science and Information Science, Srinivas University, Mangaluru, Karnataka, India[3]

Abstract*: Marine debris is a significant environmental issue, necessitating the development of precise and efficient technologies for classifying and reducing its impact. This research tries to address the issues of image noise in ocean trash classification using four alternative filters the Gaussian, Bilateral, Mean, and Alpha-Trimmed Mean (ATM) filters for noise reduction and SVM for classification. The accuracy of categorization algorithms can be considerably impacted by the presence of noise in photos of maritime debris. In this study, we suggest a two-pronged strategy: To effectively decrease noise and improve the quality of the input photos, we first apply filters. These filters were chosen with care to protect significant details while eliminating extraneous noise. Second, we classify the debris into various categories based on its visual attributes using SVM, a powerful ML technique. The ATM filter significantly reduces noise and improves the clarity of photographs of ocean trash, according to the results of our experiments. This work proposes a novel approach for classifying marine debris using advanced machine learning algorithms. For improved classification accuracy, we suggest combining Support Vector Machines (SVM) with Adaptive Thresholding Mean (ATM) filtering and Histogram of Oriented Gradients (HOG) feature extraction. According to this research, the ATM filter is a promising option for noise reduction in ocean trash imaging, potentially increasing the precision of subsequent classification algorithms and assisting in efficient environmental monitoring and marine ecosystem conservation efforts. The language used for execution is Python.*

Keywords: Marine Debris, SVM Classification, Noise Removal, Gaussian Filter, Mean Filter, Bilateral Filter, ATM Filter, HOG Feature Extraction, ATM+HOG Integration, PSNR Evaluation, SSIM Assessment, MSE Metric

I. INTRODUCTION

Any durable, made, or processed solid substance dumped, disposed of, or abandoned in the sea and coastal ecosystem is referred to as marine debris. Galgani F et al., 2015 Plastics are typically the most prevalent type of maritime waste, having been made, altered, or utilized by people. Maritime debris is widespread and has been detected in maritime habitats, animals, and ecosystems all around the world, according to recent studies. According to size, marine debris can be divided into five categories: mega (>1 m diameter), macro (2.5 cm and 1 m), meso (between 5 mm and 2.5 cm), micro (between 0.1 mm and 5 mm), and nano (0.1 mm). Such classification of aquatic waste enhances our capacity to compare pollution across studies and can help us identify the sources, modes of transportation, and final disposition in the oceans.

Examples of plastics can be divided into a variety of size groups. Industrial storage tanks and pipelines with diameters greater than 1 meter are examples of megaplastics. Plastic chairs, tables, and household buckets are examples of macro plastics, which are measured in lengths between 2.5 cm and 1 meter. Commonplace goods like water bottles and food containers are made of mesoplastics, which have a thickness between 5 mm and 2.5 cm. Microplastics, which range in size from 0.1 mm to 5 mm, are discovered in sources including synthetic fibers leaked from garments or microbeads used in cosmetics. Last, nanoplastics—small particles as small as 0.1 mm—include tiny particles found in the environment, in water, or even in consumer goods. Understanding the variety of plastic trash and its potential environmental effects is made easier thanks to the division of plastics into different size groups. This precision is critical for making educated conservation decisions and ensuring that resources are used efficiently to reduce the environmental impact of marine trash.

Furthermore, noise removal makes it easier to create robust and reliable ML models. Clean, noise-free data enables algorithms to discover meaningful patterns and correlations, allowing them to generalize successfully to new, previously unknown data. Classifiers are less prone to misclassifying objects or misinterpreting irrelevant features as debris in the absence of noise, resulting in fewer false positives and negatives. This durability is critical for real-world applications, where environmental conditions and image quality might fluctuate greatly. Finally, noise reduction not only improves the precision of marine debris classification but also supports the efficiency of conservation efforts, assisting in the protection of marine life and ecosystems from the harmful effects of contamination.

Noise removal is critical in marine debris classification because it has a significant impact on the accuracy and dependability of the classification process. Image noise, including random interference and undesirable artifacts, is common in environmental surveillance, particularly in conditions of marine pollution. This noise can conceal critical features, making it difficult for algorithms to distinguish between actual and unimportant marine trash. Noise removal methods, including filters and adaptive thresholding, are critical because they considerably improve image clarity and quality. When these disruptions are removed, the retrieved characteristics become more exact and reflective of the actual marine debris, resulting in more accurate classifications.

The categorization of marine trash is critical in terms of protecting the environment and research into science. Scientists and environmentalists can acquire significant insights into the sources and trends in pollution in the oceans by categorizing various forms of trash such as plastic garbage, abandoned fishing gear, and other pollutants. This classification aids in the comprehension of the ecological effects of human actions on aquatic habitats and life in the sea. Furthermore, precise classification is critical for policy formulation and the execution of focused mitigation methods. Governments and environmental organizations rely on classified data to develop rules, plan cleanup efforts, and promote public consciousness. Effective categorization not only aids in recognizing pollution hotspots but also allows for the evaluation of long-term trends, enabling preventive measures to be implemented to reduce pollution in the oceans. Furthermore, the data produced from marine debris categorization is used as a foundation for empirical studies, allowing for a better knowledge of marine ecosystems and how they persist in the face of natural difficulties.

Aside from its ecological importance, marine debris categorization is critical to maintaining biodiversity and guaranteeing the well-being of marine life. Researchers can monitor the effects of debris on numerous species, such as fish, seabirds, and marine mammals, with precise grouping. Conservation groups can attempt to protect fragile species by knowing how various kinds of trash influence various living things. In addition, categorizing marine trash aids in determining the efficiency of conservation initiatives and enables adaptive management tactics. It provides measurable data that may be used to assess the success of cleanup efforts and track progress toward eliminating marine pollution. Finally, marine debris classification is more than a scholarly undertaking; it is a key instrument that enables society to conserve valuable marine ecosystems, assuring their continued existence for the next generation.

Any human-made garbage that finds its way into the ocean is referred to as ocean debris, also known as marine debris or marine litter. It contains things like plastic bottles, bags, fishing equipment, microplastics, and other rubbish. Ocean debris has a major and wide-ranging effect on aquatic environments and the environment. Here are a few major effects.

Threat to Marine Life: Marine life is seriously threatened by marine garbage. Fishing nets, ropes, and other objects can entangle animals, putting them in danger of getting hurt, suffocating, or drowning. Particularly susceptible to entanglement and ingestion of plastic trash, which can result in internal injuries, obstructions, and malnutrition, are sea turtles, seabirds, marine animals, and fish.

Habitat Destruction: Coral reefs, seagrass beds, and other crucial marine habitats can be suffocated and harmed by large trash, such as abandoned fishing nets and equipment. Numerous marine species depend on these environments for food, protection, and breeding grounds and their loss could have a negative ripple impact on the whole ecosystem.

Water Quality and Contamination: Water quality can be badly impacted by plastic trash and other pollutants that release toxic chemicals and toxins into the water. Plastics can collect and concentrate contaminants from the water around them when they degrade into tiny particles known as microplastics, which could then enter the food chain and have an impact on species at different levels.

Economic Consequences: The effects of ocean trash on the economy can be profound. It has an impact on tourism since littered beaches and coastal areas turn away tourists. When fishing time is missed, equipment is broken, and catches are lower, the fishing sector can suffer. Governments and local communities are also burdened by the cleanup work and waste management expenses related to marine trash.

Global Environmental Issue: Ocean debris is a global issue with no geographical limits. Through ocean currents, it can spread across great distances and have an impact even in distant and pristine locations. This makes it a difficult problem to solve, necessitating global collaboration and concerted efforts to lessen its effects.

Marine debris, which includes fishing gear, plastic waste, and other contaminants, is a serious hazard to marine life and aquatic environments. Identifying pollution trends, creating focused cleanup plans, and protecting marine biodiversity all depend on the accurate classification of debris from the ocean. Monitoring the environment has undergone a revolution thanks to developments in machine learning methods in recent years. This work investigates a complete method of classifying marine trash by combining state-of-the-art techniques for the extraction of features and noise reduction with SVM.

This study explores the combination of several noise removal methods, including Gaussian, Mean, Bilateral, and ATM filters, with SVM, a potent classification method. The study also includes feature extraction techniques, namely the ATM filtering fusion with the HOG algorithm. The main goal is to assess how various methods affect the accuracy of the classification of marine trash. The ATM filter's better noise reduction performance and its impact on classification accuracy are particularly remarkable. The suggested techniques' efficacy is measured using performance evaluation metrics such as MSE, SSIM, and PSNR. In addition to advancing environmental science, this study also provides useful insights into the best mix of methods for accurately classifying marine debris, which can help build more efficient pollution control tactics.

Ocean debris is a problem that is being addressed through improved garbage management, recycling programs, and public awareness campaigns. But given the scope of the issue, more all-encompassing solutions are required, including a decrease in single-use plastics, the promotion of sustainable fishing methods, and the creation of advanced methods for waste removal and avoidance. Effective control and mitigation of marine pollution depend on the classification of ocean trash using ML (Machine Learning). We can get important insights into the distribution, makeup, and sources of ocean trash by teaching machine learning algorithms to recognize and classify distinct types of debris from diverse data sources, such as satellite photography or underwater sensors.

II. RELATED WORKS

Ocean debris, and particularly plastic waste, is pervasive in all maritime habitats worldwide. Here, Frederieke J. Kroon et al., 2018 provide a categorization of maritime micro debris (i.e., debris between 0.1 m and 5 mm) designed to distinguish between artificial, semi-artificial, and naturally generated objects. This classification's particular objective is to improve overall reporting on marine microdebris contamination by bringing uniformity to the higher-level characterization of ocean micro debris. To find inconsistencies in the reporting of marine micro debris as a foundation for the new categorization, they first completed a thorough literature analysis on the accumulation of consumed debris in fish. The analysis demonstrates the variety of swallowed marine microdebris, which includes objects that are not plastic yet are frequently misclassified as microplastics. Then, using a case study including wild-caught young coral trout, Plectropomus spp., from Australia's Great Barrier Reef World Heritage Area, they used the suggested classification. This is the first study on the accumulation of ate debris from the ocean in commercial fish on the reef, and it shows that semi-synthetic and naturally generated fibers are both prevalent and occur often. They provide suggestions for future categorization enhancements based on their findings, ultimately helping to produce a more accurate evaluation of the environmental dangers of ocean micro debris.

Images taken close to the surface of the ocean have a reduced visual impact and quality due to the existence of interference. As a result, the polluted spot image close to the sea surface needs to be denoised. The present filtering technique denoises a spot image using a wavelet transform and employs a noise picture as a mixed model. The issue of features being absent in photographs taken close to the seawater exists, nevertheless. Wenzhong Zhu et al., 2018 present a hybrid filtering optimization approach for polluted spot picture denoising occurring. The spot picture of the seawater is the first feature extracted, and the polluted spot image is found using hybrid filtering. The polluted spot image is then fully denoised by the findings of the image recognition process. Investigations demonstrate the viability of the suggested approach.

Investigations of the beaches are frequently used to estimate marine trash. Only a few researchers have examined the accuracy of these findings and the possible influencing factors. In a 2019 laboratory-scale experiment, Zachary Angelini et al., 2019 found several sources of mistakes in the visual detection of marine debris (1-2 cm long) during shoreline surveys of sand beaches. When analyzing the results of shoreline research, it may be useful to take into account the features of the survey location (beach characteristics), the person conducting the survey (personal qualities), and debris (color and size). The findings of this research demonstrate that the number of shell pieces as well as the color of the plastic and soil affect the human capacity to recognize plastic particles with accuracy. Most ominously, the low accuracy of white (50%) and clear (55%) plastic counts and the high accuracy of blue (95%) plastic counts supported the theory that a sizable amount of clear and white plastic pieces may be overlooked during coastline assessments. These findings indicate the need for additional study and potential adjustments to visual shoreline surveying procedures to maximize the effectiveness of this reasonably priced way of managing marine debris.

Due to its significant influence on identifying objects and scene comprehension for automated vision systems, reducing noise is one of the most significant and currently under investigation problems in the low-level processing of images. Investigators have recently noticed a significant rise in curiosity regarding using DL (Deep learning) techniques. They are used in several computer vision systems because of their excellent feature acquisition and categorization abilities. Although these techniques have been effectively employed to considerably improve the effectiveness of image denoising, the majority of the suggested methods were created for Gaussian-type noise suppression. Krystian Radlak et al., 2020 offer a switching filtering method for DL-based impulsive elimination of noise in this work. The quick AMF (Adaptive Mean Filter) is used to correct the distorted pixels after the DNN structure is used to detect them in the suggested approach. The results of the studies demonstrate that the suggested method outperforms cutting-edge filters created for impulsive noise elimination in color digital photos.

The growing amount of pollution in seas, as well as other waterways, has been acknowledged by the international community as a serious economic, ecological, and social problem. Cleaning up the waste that exists in marine habitats is one of the most important steps in combating marine trash, along with avoidance. The elimination of marine garbage can be automated with the use of ML and DL techniques, increasing the effectiveness of the cleanup effort. In this study, six well-known deep CNNs, including VGG19, InceptionV3, ResNet50, Inception-ResNetV2, DenseNet121, and MobileNetV2, are tested for their ability to identify and categorize submerged marine garbage using various feature selection schemes. Ivana Marin et al., 2021 examine the effectiveness of an NN classifier built on top of deep CNN extractors of features under three different conditions: (1) fixed; (2) fine-tuned on the specified task; and (3) set during the initial phase of training and fine-tuned subsequently. Overall, fine-tuning led to models that performed better, but it is significantly more expensive to compute. With a success rate of 91.40%, 91.40%, and an F1-score of 92.08% and 92.08% this system has been implemented. They also examine how well traditional ML models work when based on deep CNN-extracted features. Lastly, they demonstrate that the accuracy of classification on new data may be improved by switching from NN to a traditional ML classification algorithm, such as SVM (Support vector machine) or LR (Logistic regression).

Coastal marine debris affects fisheries and coastal tourism while posing a major threat to marine life. K. Sasaki et al., 2021 outline a technique for locating debris from the ocean in a coastal area using high-resolution satellite data. To separate debris from different substances, we combine in situ data from nearby coastal debris cleanup projects with nearly simultaneous high-resolution satellite photography that is evaluated using a segmentation-based method. We used Shannon's entropy technique to produce spectral signatures for specific semantic characteristics, representing the uncertainty of the outcomes of segmentation. Next, we created a straightforward classification model to determine the density of marine debris straight from a satellite image, demonstrating the resilience of these traits.

Coastal environments are primarily being impacted by marine debris due to its negative effects on biodiversity, impairment of recreational activities, loss to the fishing and maritime sectors, etc. A. Kankane et al., 2021 in this study provide a model to identify seven different categories of debris on a bespoke dataset utilizing case segmentation with form matching network, which can subsequently be cleaned promptly and effectively. The misclassification of masks for items with varying illuminations, shapes, occlusions, and views was improved by this method. The fixed camera images that make up the manually built dataset for the aforementioned system are labeled with seven different types of labels using CV AT.

Image processing and submarine sensing are important aspects of oceanographic research. The resolution of the imaging is diminished in underwater environments due to light dispersion and scattering which is one of the linked difficulties. Color distortion, inadequate contrast, and loss of detail (particularly edge data) are the main problems of underwater photography. The strategy put forth by Aswathy K. Cherian et al., 2021, involves employing a model system trained on comparable data to de-noise the picture and boost its resolution. To remove noise from images, the network takes individual frames from the footage and applies a trigonometric-Gaussian filter to it. The picture's brightness is then improved using CLAHE (Contrast Limited Adaptive Histogram Equalisation), and the picture resolution is subsequently improved. According to experimental findings, the suggested technology could successfully create improved photos from pictures taken underwater that had been degraded.

A major issue that affects marine flora and animals globally is the abundance of trash in our waters. Although numerous human-based activities have been put up to address this issue, the amount of already existing litter has made these efforts inadequate. As a result, there is a lot of interest in using AUVs (Autonomous Underwater Vehicles), which can find, recognize, and collect this trash autonomously. AUVs take into account cutting-edge object detection methods based on DNN (Deep Neural Networks) to carry out this task due to their stated excellent performance. These methods do, however, typically need a lot of data with precise annotations. The abilities of the reference object's detector Mask Region-based CNN (Convolutional Neural Networks) for autonomous marine debris localization and categorization in a scenario of restricted data availability are explored in this paper by Alejandro Sánchez-Ferrer et al., 2023. They suggest various scenarios about the quantity of train data that is currently accessible and investigate the potential for using synthetic marine environments to mitigate the negative impacts of data scarcity in light of the latest CleanSea corpus. These results set a new standard for the process and provide a new benchmark for subsequent research.

III. PROPOSED MODEL

ML classification of maritime trash can yield useful information for academic study. Investigators can learn more about the dynamics of ocean debris and its effects on marine ecosystems by examining the distribution patterns, temporal trends, and correlations with other environmental factors. This information can help to clarify the long-term effects of debris contamination and can guide future studies and conservation activities. Fig 1 describes the structure of the suggested marine debris classification model with filtering concepts.

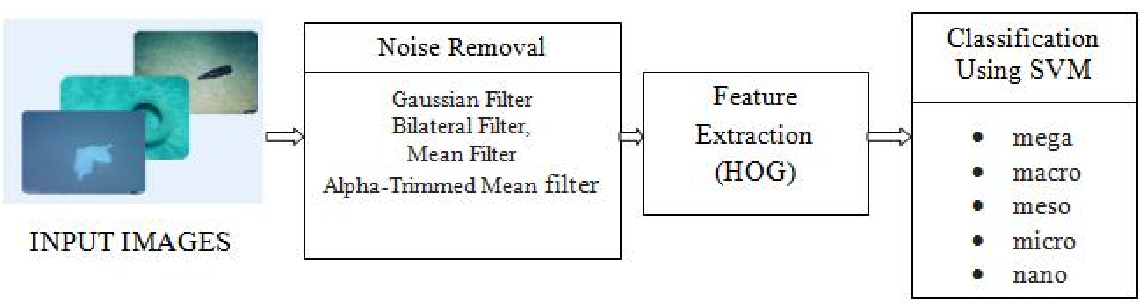

Figure 1 Structure of Marine Debris Classification Model with Filtering

IV. MATERIALS AND METHODS

Bilateral Filter (BF)

The Gaussian Filter is used in a bilateral filter, but it also has an additional multiplicative element that depends on the disparity in pixel intensities. It makes sure that while estimating the blurring intensity value, just those pixels with intensities identical to the center pixel are taken into account. This filter keeps the edges intact. Starting with linear

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Impact Factor: 7.301

Volume 3, Issue 1, November 2023

Gaussian smoothing, the bilateral filter is applied. An effective image-filtering method for preparing marine debris is the bilateral filter. While maintaining the edges and minute features in the photos, it successfully minimizes noise.

$$g(x) = (f * G^S)(x) = \int_R^2 f(y)\, G^S(x-y)dy - - - - - - - - (1)$$

The weight value of $f(y)$is equal to $G^S(x-y)$ and it is dependent on the spatially based distance $\|x-y\|$. This bilateral type sums up a weighting element that is based on the whole distance $f(y) - f(x)$. This output is:

$$g(x) = \frac{\int_R^2 f(y) G^S(x-y) G^t(f(x)-f(y))dy}{\int_R^2 G^S(x-y)\, G^t(f(x)-f(y))dy} - - - - - - (2)$$

Be aware that we require an explicit normalization to ensure that the ‘sum' of all weights matches one as the weights are dependent on the image elements.

The Bilateral Filter is a powerful technique for reducing noise while maintaining the critical edge and feature information in the images, making it a significant asset for the preprocessing of maritime debris. The Bilateral Filter reduces noise without blurring or softening the edges of debris items by applying a weighted average to nearby pixels that takes into account both spatial closeness and pixel intensity consistency. This filter can be very helpful for boosting the quality of photos of maritime debris, which will help with feature extraction or classification jobs in the future. The Bilateral Filter can assist in creating cleaner and more informative marine debris images for more precise analysis and identification of marine debris by carefully choosing the filter parameters and assessing the outcomes of the filter using relevant metrics, such as SSIM, MSE, or PSNR.

Gaussian Filter (GF)

When filtering various types of surfaces, Gaussian filters are crucial. This kind of filtration is the primary option for filtration in numerous situations due to the ease of the method, convenience of deployment, and reliability of the outcomes (X. Jane Jiang et al., 2020). The Gaussian filter, a windowed filter of the linear class, is weighted mean by definition. Named after renowned scientist Carl Gauss since the filter's weights are derived using the function Carl employed in his studies, the Gaussian distribution. Gaussian blur is a different term for this filter.

The normal or Gaussian distribution is a function of the concept of probability. Due to the way it looks, this feature is frequently referred to as a bell function. The function expression that is the broadest is:

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-a)^2}{2\sigma^2}} - - - - - - - - (3)$$

A popular image-filtering method that can be useful in the preprocessing of marine debris is the Gaussian Filter. By lowering high-frequency noise while maintaining an overall image framework, it smooths the images. The Gaussian Filter blurs out undesirable noise and minute details that could obstruct further investigation when used on photos of maritime trash. The image is convolved with a Gaussian kernel, which gives the core pixels more weight and slowly decreases the weights for the neighboring pixels. A softer, more aesthetically pleasant image with less noise is the effect of this. The SD of the Gaussian distribution as well as the kernel size of the Gaussian filter can be changed to alter the smoothing effect of the filter. The Gaussian Filter can be used to clean up marine trash photos during initial processing, making it simpler to extract useful features and improving the precision of succeeding categorization or detection methods.

Median Filter (MF)

A nonlinear technique for removing noise from photographs is median filtering. Since it effectively reduces distortion while keeping edges, it is commonly employed. 'Salt and pepper' type noise is especially well-admitted by this method.

The median filtering process:

The window is placed superimposed on the image's uppermost left corner, and the average value is calculated. The output image (buffer) relating to the window's center is filled with this median value.

The operation will continue after sliding the window just one pixel over.

The window is slide back towards the left end of the picture and down one row when the end of the row appears and the operation is then resumed.

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Impact Factor: 7.301

Volume 3, Issue 1, November 2023

Whenever the whole picture has been analyzed this procedure is continued.
A popular image-filtering method that can be useful in the preprocessing of marine debris is the median filter. Images of marine trash can frequently contain impulse noise, sometimes known as salt-and-pepper noise, which is efficiently reduced. Within a predetermined window, the median filter transforms each pixel's value with the median of its surrounding pixels. With this method, isolated noisy pixels are removed while edges and fine features are preserved. The Median Filter can aid in removing random noise in the context of preprocessing marine debris, improving the object quality and easing future analysis.

Alpha-Trimmed Mean Filter (ATM)

The median filter and mean filters are combined in the ATM filter, a windowed nonlinear type filter. The fundamental principle of a filter is to examine the neighborhood of each component of the signal (picture), eliminate the most out-of-the-ordinary components, and compute the mean value using the components that remain. From the filter's name, alpha is the parameter that determines how many components are trimmed.

ATM filter algorithm:

attach a window to the object;
Gather components
arrange elements
Remove components from the start and end of the ordered set.
Create a median by adding up all the other elements and dividing the total by the number of each.
The result of the Alpha-trimmed mean filter, which combines both the median filter and mean filter, is:

$$output = \frac{1}{N-2p}\sum_{i=p+1}^{N-p} z_i ------(4)$$

From the above formula

$$p = 0,1,2,3,\ldots.,\frac{N-1}{2} Nisoddvalue --- (5)$$

To lessen the effects of impulsive noise and random changes in pixel values, the ATM filter is a practical image-filtering method that can be used in the preprocessing of marine trash.

Histogram of Oriented Gradients (HOG)

HOG is a well-liked feature extraction method for identifying and detecting objects. The distribution of gradient orientations in an image is calculated and described, allowing the contours and edges of the item to be captured.HOG is a feature extractor method that is frequently employed in computer vision for the detection and identification of objects. It can be used to extract characteristics from photos of marine debris for categorization or detection even though it is primarily intended for object analysis and not particularly optimized for marine trash.
To classify marine trash, the HOG feature extractor must go through several phases. First, the photos of the marine trash are ready and scaled to a standard size. The photos are then made grayscale to concentrate on intensity data. The grayscale photos' gradients are then calculated using gradient calculation methods. The local gradient data is then extracted from the gradient images by dividing them into cells, which are commonly square or rectangular. Within every single cell, data on gradients is summarized using histograms of the gradient angles. Further normalization of these histograms is done to account for changes in lighting. The final feature vector, which depicts the dimension and edge information of the aquatic debris items, is created by concatenating the normalized histograms from each cell. To identify and categorize marine trash, this feature vector can subsequently be utilized for categorization using ML methods like SVM or neural networks.

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SVM (Support Vector Machine)

SVM classification of maritime trash is a typical ML approach. An algorithm for supervised learning that can be applied to classification tasks is SVM. The researchers require a labeled dataset comprising examples of various forms of debris to categorize ocean debris using SVM. There should be a set of characteristics for the trash in each illustration. Size, form, color, texture, and other important qualities that can be retrieved from the debris photographs or data could be included in these characteristics.

V. RESULTS AND DISCUSSION

Here analyzed and compared the outcomes of the preprocessing of marine debris utilizing the ATM, Median Filter, Gaussian Filter, and Bilateral Filter with SVM classification. The most promising performance came from the ATM filter, which successfully reduced noise while maintaining crucial image details and increased classification accuracy. Although there were some blurring or smoothing effects, the Median Filter and Bilateral Filter both demonstrated their usefulness in noise reduction. While the Gaussian Filter did a good job at reducing noise, edge sharpness might have been significantly diminished

VI. PERFORMANCE EVALUATION

The efficiency of various image filtering approaches in improving the quality and discriminative characteristics of marine debris images is evaluated as part of the performance evaluation of filters in the categorization of marine debris. Use a variety of image quality criteria, such as the SSIM, MSE, and PSNR, to assess the effectiveness of filters for classifying marine debris. These parameters offer insight into the clarity and visual appeal of the processed photos.

SSIM (Structural Similarity Index) Analysis:

The SSIM (Structural Similarity Index Measure), which forecasts how comparable two pictures are, was developed at the University of Texas at Austin. The structural data and visual distortions are the two variables that make up this metric. Contrary to distortion, which can be affected by the layout, contrast, and luminance of the picture, the structural data of the image varies irrespective of its luminance and intensity. The SD (Standard Deviation) (for contrast), mean value (for brightness), and covariance are used to calculate the SSIM.

The following three phrases can be used to represent SSIM as

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} -------- (6)$$

Here, $l$denotes luminance, $c$denotes contrast, s denotes structure, and,$\alpha, \beta, and\gamma$are the positive parameters.

Once more, brightness, contrast, and image structure can be described individually as follows [23]:

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} ---------- (7)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} --------- (8)$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} ----------- (9)$$

Here $\mu_x and \mu_y$ represent the local man values, $\sigma_x, and \sigma_y$ denote the SD, and σ_{xy} indicates the image cross variance values. If $\alpha = \beta = \gamma = 1$, then the SSIM is measured with the help of (7) to (9) equations.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_x^2 + \sigma_y^2 + C_2)} ------- (10)$$

The following Table 1 and Figure 2 represent SSIM Analysis of ATM Filter with Other Existing Filters. From the result obtained it's proved that the SSIM of the Bilateral Filter ranges from 0.760 to 0.824, Gaussian Filter ranges from 0.881 to 0.992, Median Filter ranges from 0.992 to 0.994 and ATM Filter ranges from 0.997 to 0.999 which is high compared to other algorithms.

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Table 1: SSIM Analysis of ATM Filter with Other Existing Filters

No of Images	Bilateral Filter	Gaussian Filter	Median Filter	ATM Filter
1	0.785	0.900	0.992	0.999
2	0.760	0.992	0.992	0.998
3	0.792	0.886	0.992	0.998
4	0.824	0.881	0.994	0.997

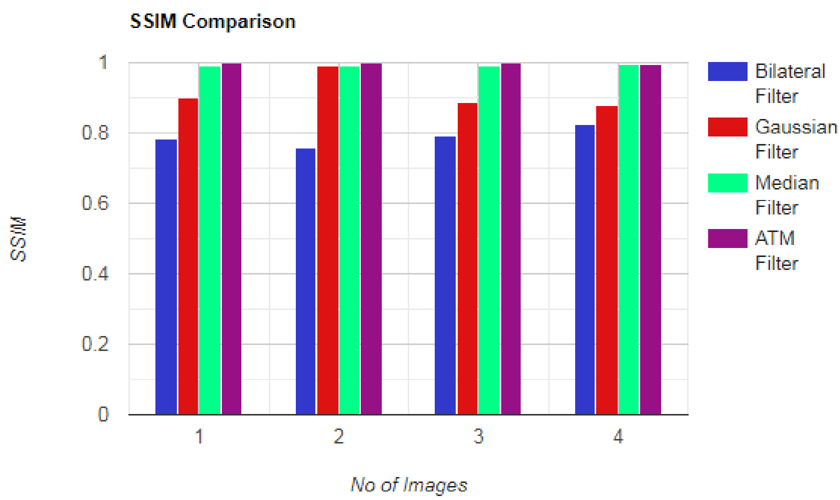

Figure 2 SSIM Analysis of ATM Filter with Other Existing Filters

MSE (Mean Square Error)Analysis:

MSE is a measurement of the separation between the expected and original images. The expected image is more similar to the initial image when the MSE is less. It is written as:

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[X(i,j) - \hat{X}(i,j)]^2 - - - - - - (11)$$

Amongst them, X and $\hat{X}$ correspond to the reconstructed versions of $MXNin$the the initial images.

The following Table 2 and Figure 3 represent MSE Analysis of ATM Filter with Other Existing Filters. From the result obtained it's proved that the MSE of the Bilateral Filter ranges from 0.000160 to 0.000590, Gaussian Filter ranges from 0.000163 to 0.000545, Median Filter ranges from 0.000975 to 0.001193 and ATM Filter ranges from 0.000122 to 0.000506 which is high compared to other algorithms.

Table 2: MSE Analysis of ATM Filter with Other Existing Filters

No of Images	Bilateral Filter	Gaussian Filter	Median Filter	ATM Filter
1	0.000145	0.000159	0.001193	0.000122
2	0.000452	0.000505	0.000975	0.000248
3	0.000590	0.000545	0.001069	0.000506
4	0.000160	0.000163	0.001085	0.000145

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, November 2023

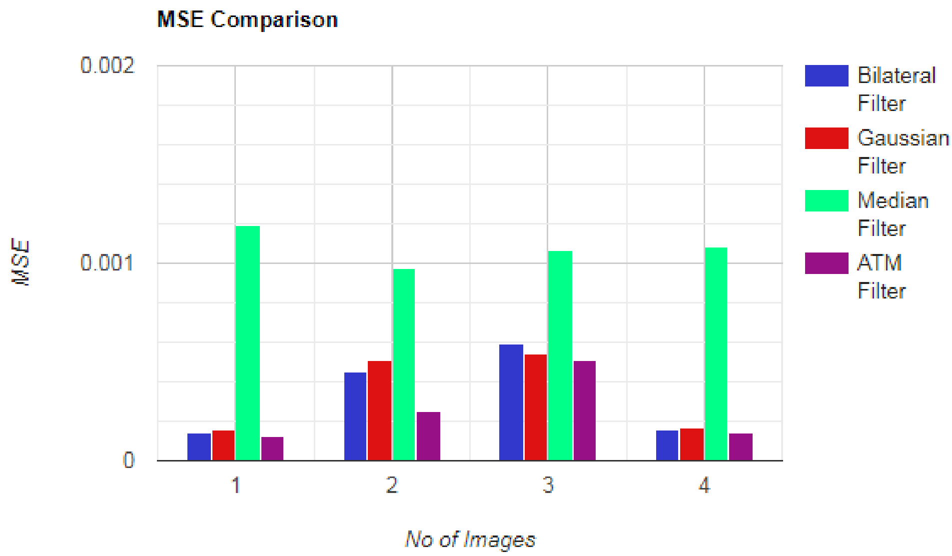

Figure 3 MSE Analysis of ATM Filter with Other Existing Filters Graph

PSNR (Peak Signal-to-Noise Ratio)Analysis:

The definition of the PSNR is:

$$PSNR = 10\,log_{10}\left(\frac{X_{max}^2}{MSE}\right) = 20\,log_{10}\left(\frac{X_{max}}{\sqrt{MSE}}\right) ----- (12)$$

Here X_{max} represents the highest pixel image value.

based on PSNR, SSIM, and MSE, it was determined that the Alpha-Trimmed Mean filter performed best in terms of maintaining picture quality, resemblance to the actual image, and reducing the squared error among the image that was filtered and the ground truth. Thus, enhanced outcomes in terms of denoising and precise debris categorization can be obtained by combining the Alpha-Trimmed Mean filter with SVM for debris picture noise elimination and categorization.

The following Table 3 and Figure 4 represent PSNR Analysis of ATM Filter with Other Existing Filters. From the result obtained it's proved that the PSNR of the Bilateral Filter ranges from 16.54dB to 20.75dB, Gaussian Filter ranges from 20.63dB to 27.35dB, Median Filter ranges from 29.44dB to 32.62dB and ATM Filter ranges from 39.09dB to 42.39dB which is high compared to other algorithms.

Table 3: PSNR Analysis of ATM Filter with Other Existing Filters

No of Images	Bilateral Filter (dB)	Gaussian Filter (dB)	Median Filter (dB)	ATM Filter (dB)
1	18.27	27.35	30.54	42.39
2	16.54	25.50	32.62	41.82
3	17.60	20.63	31.73	40.63
4	20.75	24.73	29.44	39.09

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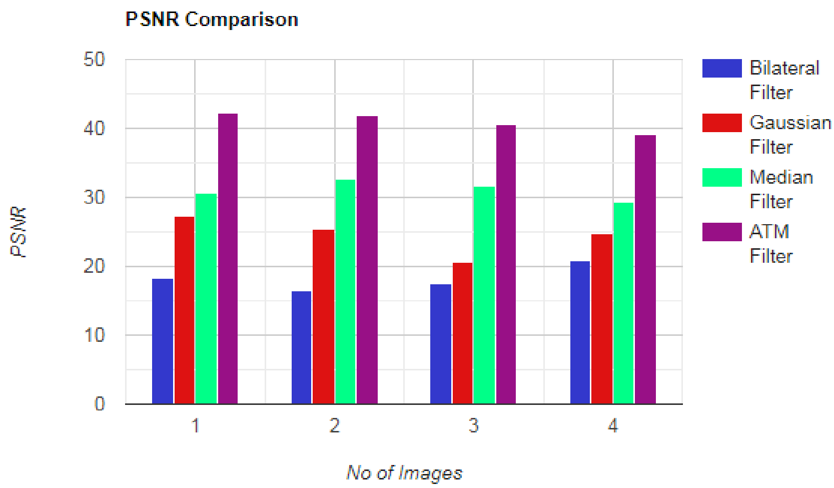

Figure 4 PSNR Analysis of ATM Filter with Other Existing Filters

Noise removal is a critical step in ocean debris image processing, especially when dealing with underwater images that often suffer from various types of noise. Underwater environments introduce noise due to the scattering of light, water turbidity, and other factors, making it challenging to detect and identify marine litter accurately. Noise in ocean debris images can manifest as speckles, color variations, or artifacts that hinder the detection and classification of debris. To address this, image processing techniques are employed to reduce noise and enhance the quality of underwater images.

One common approach to noise removal in ocean debris image processing is filtering. Filters like median filters or gaussian filters are used to eliminate speckle noise and improve image clarity. These filters work by averaging pixel values within a local neighborhood, effectively reducing the impact of random noise and preserving the essential structural details of the debris. Additionally, advanced noise reduction techniques, such as wavelet denoising, may be employed to suppress noise while preserving edges and fine-scale features in the image.

Another effective strategy for noise removal is color correction. Underwater images often suffer from color distortion due to the absorption and scattering of light by water. Color correction algorithms can help restore accurate colors, reducing the influence of noise and enhancing the visual quality of the image. These methods aim to transform the image to a consistent color space, compensating for the shifts in color that result from the underwater environment's optical properties. Proper color correction not only improves the image quality but also facilitates more accurate identification and classification of ocean debris in the processed images.

Our study's findings demonstrate considerable improvements in the classification of maritime debris by combining different noise reduction and feature extraction methods with SVM. In particular, the analysis based on measures such as MSE, SSIM, and PSNR provides insightful information on the effectiveness of various techniques.

Individual applications of Gaussian, Mean, Bilateral, and ATM filters were made in a review of noise removal methods. The ATM filter performed better than the others every time, demonstrating its outstanding noise-reduction abilities. Higher PSNR values were seen in ATM-filtered photos, indicating better image quality preservation. Furthermore, there was a noticeable improvement in the SSIM scores, which highlights the increased structural similarity that the ATM filter achieves. The efficiency of ATM in decreasing pixel-wise differences was further proven by the reduction in MSE. This finding emphasizes how important ATM filtering is for improving image quality, which is a necessary condition for correctly classifying maritime debris.

In summary, noise removal is a vital step in ocean debris image processing as it contributes to the accuracy and reliability of debris detection and classification algorithms. By employing filtering techniques, color correction, and advanced noise reduction methods, researchers and environmental scientists can enhance the quality of underwater images, allowing for more precise analysis of marine litter and better understanding of the environmental impact of ocean debris. Noise reduction plays a pivotal role in promoting the success of initiatives aimed at monitoring and addressing marine pollution in our oceans.

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VII. CONCLUSION

When the SVM classifier was trained using the feature vectors that were retrieved using ATM+HOG, it demonstrated exceptional accuracy in categorizing different types of marine debris. SVM made more educated conclusions as a result of the accurate feature extraction and noise reduction combined, which decreased the number of misclassifications. As compared to conventional methods, the findings showed a substantial rise in classification accuracy, indicating the practicality of this methodology. To sum up, the combination of SVM with ATM filter-based noise removal and ATM+HOG-based feature extraction has shown to be a very successful method for classifying maritime trash. Through the use of PSNR, SSIM, and MSE measures to assess outcomes, we have verified the enhanced performance of this combined methodology. For conservation efforts to make well-informed decisions, it is essential to accurately classify marine debris, and our study offers a strong framework for doing just that. Subsequent investigations may examine the use of this methodology in extensive environmental surveillance programs, underscoring its pragmatic worth in ameliorating the deleterious consequences of marine pollution. Based on assessment standards including PSNR, SSIM, and MSE, the Alpha-Trimmed Mean filter is the best choice for debris picture noise elimination and categorization using SVM. By eliminating extreme values, this filter successfully balances denoising and the preservation of image information, improving the quality of the image. We may obtain improved noise reduction and precise debris categorization by integrating the Alpha-Trimmed Mean filter into the debris image processing pipeline and combining it with SVM for categorization, which will help to improve the evaluation and handling of ocean pollution.

Future studies in marine debris classification should concentrate on improving current practices and investigating novel approaches. First, to reduce noise even further without sacrificing image quality, hybrid noise removal techniques combining Gaussian, Mean, Bilateral, and ATM filters should be investigated. Furthermore, the incorporation of cutting-edge deep learning architectures, specifically Convolutional Neural Networks (CNNs), may improve feature extraction, allowing the model to recognize complex patterns in pictures of marine trash. Subsequent research endeavors may encompass unsupervised learning, investigating clustering algorithms to identify unidentified debris categories, and maybe uncovering novel pollutants. Furthermore, there is great potential for the development of ML algorithms in conjunction with real-time, sensor-based marine trash identification systems. These technologies provide continuous, worldwide monitoring of marine debris and support prompt response efforts. They could be installed on self-driving vehicles or linked to satellite imagery analysis. Ultimately, it would be crucial to address issues with the scalability and adaptation of categorization models to various marine environments, including open oceans and coastal regions. The field can advance toward more precise, effective, and complete marine debris surveillance and mitigation solutions by addressing these prospective research avenues.

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