RE-2022-212909 - Turnitin Plagiarism Report

by Srinivasan M

Submission date: 07-Mar-2024 10:38AM (UTC+0200)
Submission ID: 271709820632
File name: RE-2022-212909.docx (656.85K)
Word count: 3941
Character count: 23950

Microplastic Ingestion in the Human Body using Deep Learning

Gunavathie M A[1]
Information Technology
Panimalar Engineering College
Chennai, India
gunavathie.ap@gmail.com

Srinivasan M[2]
Information Technology
Panimalar Engineering College
Chennai, India
srinimuthu80@gmail.com

Thirushanth Karthikeyan G[3]
Information Technology
Panimalar Engineering
Chennai, India
thirushanth2003@gmail.com

Praveen D[4]
Information Technology,
Panimalar Engineering College
Chennai, India
praveenpraveen82726@gmail.com

Jaivardhan G [5]
Information Technology,
Panimalar Engineering College
Chennai, India
jaguarjai333@gmail.com

***Abstract*—This study explores the ubiquitous problem of microplastics, which are tiny plastic particles smaller than five millimeters and have emerged as a major environmental concern. Microplastics are dangerous to the environment and public health because they pollute food chains and enter ecosystems. The degree to which microplastics penetrate the human body is still a developing concern, despite the fact that their effects on marine environments have been thoroughly investigated.This study examines the mechanisms of ingestion, inhalation, and skin contact as they relate to human exposure to microplastics. We specifically focus on the consumption of microplastics and the possibility of their build-up in human tissues and organs. We present a new method that uses cutting-edge deep learning algorithms to identify and measure microplastics in biological samples. The main objective is to increase our comprehension of the effects of microplastics.**

***Keywords*- Microplastics,Deep learning,Automated detection,Ingestion pathways**

I. Introduction

Microplastics, which are tiny plastic particles smaller than five millimeters, are becoming a major global environmental concern. They pose serious dangers to human and environmental health as well as the fragile ecosystem balance. These minute pollutants can penetrate ecosystems, damage food chains, and survive in a variety of environmental matrixes. They originate from a variety of sources, such as industrial operations, plastic degradation, and waste mismanagement. Although the harmful effects of microplastics in marine habitats have been well-documented, there is growing concern about how deeply these particles can enter the human body, which calls for thorough investigation and knowledge.

Large-scale environmental introductions of microplastics have the sneaky potential to cross biological borders and affect aquatic, terrestrial, and atmospheric systems. The fact that they are widely dispersed and persistent across a variety of environmental niches highlights how urgent it is to address this problem. Microplastics break down and fragment in aquatic environments, producing tiny particles that can more readily enter the food chain and impact a range of marine life. As a result, human populations that depend on these marine resources are also affected, which could provide a method for microplastics to enter the human body.

The existence and possible buildup of microplastics in the human body is a key aspect of the microplastics puzzle that this study focuses on. Microplastics can be ingested, inhaled, and come into touch with the skin as the main ways that humans are exposed to them. The propensity for microplastics to accumulate in tissues and organs, so raising concerns about their long-term health effects, makes ingestion the most concerning of these. Because of this, the focus of this research is on the ingestion pathway with the goal of clarifying the degree of microplastic ingestion, their location throughout the human body, and the possible health hazards linked to this ubiquitous exposure.

The choice to concentrate on the ingestion pathway was made due to its importance in the overall scenario of human exposure, which is influenced by food sources that are contaminated, dietary practices, and the environmental persistence of microplastics. By doing this, we hope to provide insightful information that will help guide strategies for reducing the health concerns associated with microplastics and open the door for the advancement of efficient detection and analysis techniques. This study aims to close a significant knowledge gap by elucidating the intricate interactions between microplastics and human systems. This will enable well-informed policy and decision-making to protect the environment and public health.

II. EXISTING SYSTEM

Under the current system, labor-intensive, traditional laboratory techniques like spectroscopy and microscopy are mostly used to analyze microplastics in human samples. Although these techniques are useful for recognizing and describing microplastics, they have several significant disadvantages. Because these processes are manual, they take a long time to complete and require a lot of human resources at different stages, such as sample preparation, analysis, and data interpretation. This labor-intensive nature by nature creates difficulties when working with big sample sizes and carrying out in-depth research.

Moreover, subjectivity is introduced into the analysis by depending so heavily on human observation, which increases the risk of errors and lowers the overall accuracy of the findings. The shortcomings of these manual methods highlight how urgently novel solutions to these problems are required. The identification and quantification of microplastics in human samples need a more effective, precise, and scalable approach. This requirement has sparked research into cutting-edge technology, especially deep learning, to automate and improve the analytical process. This represents a major step forward in overcoming the drawbacks of the existing manual approaches.

III. PROPOSED SYSTEM

By providing a Deep Learning-Based Detection System, the suggested system offers a major advancement in the field of microplastics analysis. This novel method revolutionizes the detection and quantification of microplastics in human biological samples by fusing state-of-the-art deep learning algorithms with sophisticate[7] image and spectrum analysis techniques. Fundamentally, deep learning models—more specifically, Convolutional Neural Networks, or CNNs—are used to automatically analyze microscopic images, which makes it possible to locate and identify microplastics inside intricate biological matrices.
The technology excels at automating the typically labor-intensive and manual analysis procedures related to microplastics identification by utilizing deep learning. By lowering the need for human intervention, this automation not only expedites the analysis workflow but also greatly improves efficiency.

Furthermore, the suggested system gains another level of sophistication with the addition of spectral analysis. This feature makes it possible to examine microplastics in more detail than just their appearance, making it possible to identify particular polymers and improving the system's overall discriminatory power. A more thorough comprehension of microplastics in human biological samples is made possible by the synergistic combination of spectral analysis and image analysis.
This suggested system's main objective is to improve the accuracy of microplastics detection while simultaneously streamlining the analysis procedure. By minimizing the possibility of human mistake, deep learning models help to identify microplastics with a better degree of precision due to their capacity to understand complex patterns and features. The technology is positioned as a useful tool due to its level of automation and accuracy.
Essentially, this proposal's Deep Learning-Based Detection System has the potential to revolutionize the field of microplastics research by offering an advanced and effective way to overcome the drawbacks of human techniques. The suggested system, which automates the analytical procedure, advances the conversation on environmental and public health awareness while also facilitating a deeper knowledge of the health effects of ingesting microplastics.

DIGITAL IMAGE PROCESSING OVERVIEW:

This process includes modifying image data using several methods, like feature extraction and noise reduction. Understanding forms allows for the identification of objects, which is essential for tasks like identifying vehicles or cells. Managing changes in lighting and angles presents a problem.

Image Digitization:
Images are represented as arrays of pixels when processed digitally. Point, local, and global operations are examples of basic operations that enable compression, restoration, and augmentation. Similar to noise smoothing, image enhancement uses methods like median filtering. Common point procedures also include pseudo-coloring and contrast manipulation.

Object Class Recognition Challenges:
Real-world visual distortions, appearance fluctuations, and interclass resemblance make object class recognition challenging. This research uses an edge-based method for object detection and image categorization. It uses flexible combination of basic form primitives, such as ellipses and line segments, to represent object classes. These primitives efficiently match across sizes, are scale-normalized, and facilitate abstract thinking.

Innovative Object Class Recognition:
The method centered on edge information and generic shape primitives is presented in this study. It can dynamically adapt to different object classes and represents complex shapes using combinations of line segments and ellipses. These combinations, called form tokens, take advantage of geometric, structural, and shape-distinguishing limitations to offer a new approach to object class classification.

CNN ALGORITHM:
Think of a network that has network function F and a single real input, x. Two steps are involved in computing the derivative F'(x):

Feed-forward: the network receives the input x. Every node evaluates its primitive functions as well as their derivatives. There is storage for the derivatives.

Back propagation: The network is operated backwards by feeding the constant 1 into the output unit. A node receives input, adds it, and multiplies the result by the value kept in [18] unit's left half. The unit's left receives the sent result. The derivative of the network function with respect to x is the result gathered at the input unit.
CNN's architectural design.

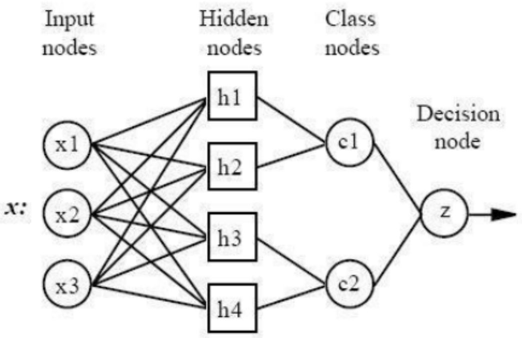

Fig.1

All CNN networks have four layers:

1.Input layer — For every predictor variable, there is one neuron in the input layer. N-1 neurons are employed when dealing with categorical variables, where N is the total number of categories. By deducting the median and dividing by the interquartile range, the input neurons, or processing that occurs prior to the input layer, normalize the range of data. The values are subsequently fed to every neuron in the hidden layer by the input neurons.

2.Hidden layer — Each case in the training data set is represented by one neuron in this layer. Together with the target value, the neuron keeps the values of the case's predictor variables. A hidden neuron uses the sigma value(s) to apply the RBF kernel function after calculating the Euclidean distance of the test case from the neuron's center point, using the x vector of input values from the input layer. The neurons in the pattern layer receive the resultant value.

3.Pattern layer / Summation layer — CNN and GRNN networks use distinct next layers in their networks. For CNN networks, a single pattern neuron corresponds to each target variable category. Every hidden neuron stores the real target category of every training example; only the pattern neuron that corresponds to the category of the hidden neuron receives the weighted value that emerges from a hidden neuron. It is a weighted vote for that category since the pattern neurons sum the values for the class they represent.

4.Decision layer —The CNN and GRNN networks have distinct decision layers. In order to predict the target category for CNN networks, the decision layer weighs the votes for each target category that were amassed in the pattern layer and uses the vote with the highest percentage.

ALGORITHM:

The required corrections are computed using the convolutional neural algorithm, which first selects the network's weights at random. The following four steps can be used to break down the algorithm:

i) Forward-looking calculation

ii) Weight updates; iii) Convolutional neural to the hidden layer; iv) Convolutional neural to the output layer

V) Software Block Diagram

Block Diagram

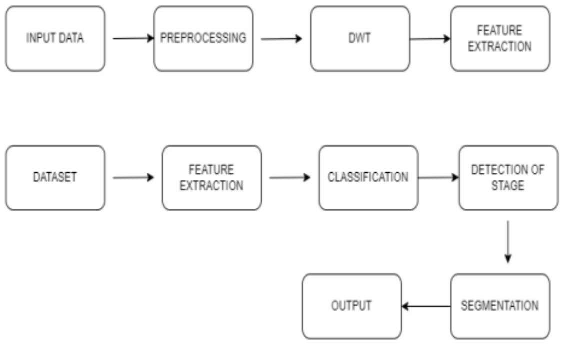

fig.2

1. Data Acquisition: A crucial first step in the process, obtaining human tissue samples may include doing biopsies or requiring other medical interventions. Understanding the existence and distribution of microplastics in the human body is based on these samples. For further studies to be reliable, the obtained samples must be guaranteed to be representative and of high integrity.

2. Initial processing:

Steps in pre-processing: The grayscale filter is used in the pre-processing stage of the block diagram presented in the project. This stage prepares the grayscale images for further analysis by applying contrast enhancement, noise reduction, and image segmentation. The method guarantees that the input data is optimal for the deep learning model by introducing the grayscale filter at this point, enabling more precise and effective microplastics detection.Essentially, the suggested system's use of a grayscale filter adds to its overall effectiveness.

microplastics analysis through data simplification, contrast enhancement, and compatibility with deep learning model capabilities. By tackling the issues with manual and labor-intensive procedures in the automated detection system, this strategic integration improves its accuracy and efficiency.

3. Examination of Images:

The microscopic images are subjected to advanced deep learning models, specifically Convolutional Neural Networks (CNNs), in the image analysis module. The main goal is to identify and locate microplastics in the intricate biological samples. Because of their superior ability to learn hierarchical features from images, CNNs are able to identify minute patterns related to microplastics, like their size, shape, and spatial distribution. To detect microplastics in biological samples, the image analysis module uses a 6-layer Convolutional Neural Network (CNN):

i) Input Layer: Microscopic images that have been grayscale-filtered are used as input, laying the groundwork for further research.

ii) Convolutional Layer: Learns hierarchical characteristics by the application of filters, capturing patterns associated to microplastics such as size, form, and spatial distribution.

iii) Activation Layer: To improve the network's capacity to represent intricate relationships within the data, non-linearities (such as ReLU) are introduced.

iv) Pooling Layer: Reduces computational effort and concentrates on essential data for effective analysis by descending samples of learnt features.
v) Fully Connected Layer: This layer links neurons to enable thorough processing of features that are extracted, enabling detailed examination of microplastics' properties.
vi) Output Layer: Provides accurate results for the detection and localization of microplastics, providing information on their size, shape, and distribution.

4. Classification: The classification module organizes the microplastics that have been detected into distinct categories or groups according to a variety of attributes after the detection phase. This could entail grouping them based on their size, shape, or polymer composition. The classification process gives the analysis more depth and a more sophisticated understanding of the variety of microplastics that are present in human tissues.

5. Microplastic identification: The microplastic identification module is the heart of the system. It uses deep learning models to analyze spectral data and photos in great detail. The method obtains a thorough understanding of the quantity and existence of microplastics in human tissues by merging data from many modalities. The multi-modal method strengthens the detecting system's resilience.

6. Results and Insights: Following the completion of the procedure, the results and insights obtained from the detection of microplastics are presented. Researchers and medical professionals are presented with these data, which include information regarding the kinds, amounts, and distributions of microplastics as well as insights into possible health effects. This action supports additional research and decision-making, adding to the current conversation around environmental and public

The research described here is a methodical approach to thoroughly investigate microplastics in human tissues by utilizing deep learning and sophisticated analytical tools. Every module contributes significantly to the field of environmental and human health research by improving and expanding our knowledge of microplastic ingestion.

ALGORITHM FLOW:

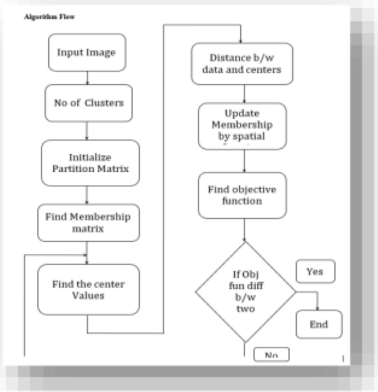

Fig.3

Initialize the Fuzzy Weights. Set the Fuzzy Weights to zero. Our method gives the user the option to initialize the weights randomly or using feature vectors in order to compare the FCM with FCFM. After assigning the first Kinit (user-given) feature vectors to prototypes, the weights are computed using Equation (4) in the process of initializing the weights using feature vectors.
Standardize the Weights over Q. Make the Weights over Q uniform. The computed cluster centers approach each other more and closer throughout the FCM iteration. Before standardizing the weights over Q, we use w[q,k] = (w[q,k] – wmin)/(wmax – wmin) to prevent the rapid convergence and constant clustering into one cluster. In the case of the specific class prototype, wmax and wmin represent the maximum and minimum weights over the weights of all feature vectors.

Eliminating Empty Clusters. Removing Vacant Groups. We include a step (Step 8) to remove the empty clusters following the fuzzy clustering loop. This phase comes before the modified XB validity computation and is placed outside of the fuzzy clustering loop. The distance of an empty cluster pair may equal the lowest distance of the prototype pair used in Equation (8) if the elimination is not performed. To ensure that the procedure only removes empty clusters, we supply 0 to the process when calling the method of removing small clusters.

Following the fuzzy c-means iteration, we add Step 9 to compute the cluster centers and the modified Xie-Beni clustering validity κ in order to compare the results and select the best one:
The product of separation measures and compactness is the Xie-Beni validity [10]. Equation (5) defines the compactness-to-separation ratio v.
$(1/K)\sum(k=1,K)\sigma k2\}/Dmin2\ \sigma k2 = \sum(q=1,Q)\mu = x(q) - c(k)$ ‖ wqkThe smallest spacing between the cluster centers is 2 Dmin.
The formula for the Modified Xie-Beni validity, κ, is $\kappa = Dmin2/\{\sum(k=1,K)\sigma k2\}$.

In contrast to the original Xie-Beni validity measure, the variance of each cluster is computed by summing over only the members of each cluster, not over all Q for each cluster. When q is in cluster k}, σk2 = ∑{q}. wqk || 2 – x(q) – c(k) Equation shows how the membership function incorporates the spatial function.

$$u'_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q}}$$

Discrete Wavelet Transform, or DWT: Using the project's microplastics data for analysis and feature extraction.
Division:
Use: Separating microplastics from biological samples so that they can be thoroughly examined.

GLCM (Gray-Level Co-occurrence Matrix) Algorithm: Algorithm extracts textural features and offers information about the properties of microplastics.

CNN (Convolutional Neural Network): Using hierarchical feature learning to analyze and identify microplastics in microscopic pictures.

SOFTWARE REQUIREMENTS:

i) MATLAB 2019: Central computing environment for implementing algorithms and processing data.

ii) picture Processing Toolbox: Enables precise microplastics detection through picture analysis, enhancement, and modification.

iii)Deep Learning Toolbox: allows complex pattern recognition using Convolutional Neural Networks (CNNs).

iv) Data Acquisition Toolbox: Effectively gathers, examines, and presents data from a range of sources.

IV. METHODS:

1. Convolutional Neural Networks (CNNs): CNNs are the main deep learning architecture used in the identification of microplastics through image analysis. These neural networks are very suitable for identifying minute patterns related to microplastics, such as size, shape, and spatial distribution, because they are skilled at automatically learning hierarchical characteristics from photographs. The network can identify local patterns thanks to the convolutional layers, and it can identify specific patterns thanks to the fully connected layers that combine this data.

2. Image Pre-processing: To improve the quality of microscopic images that are recorded, pre-processing techniques are used. This comprises:
Using filters and algorithms to lessen noise artifacts is known as noise reduction.
Contrast Enhancement: Increasing the contrast of the image to make microplastics more visible.

Image Segmentation: To enable more focused analysis, the image is divided into segments.

3. Spectral Analysis: This method looks at microplastics in more detail than just their appearance. This can involve using methods to pinpoint the precise polymers that make up microplastics, including Raman Spectroscopy or Fourier Transform Infrared Spectroscopy (FTIR). For an extra degree of distinction in the classification process, spectral data is essential.

4. Classification Models: Based on a number of characteristics, such as the following, classification models are used to group identified microplastics:
ize: Assigning dimensions to microplastic groups.
Shape: Dividing microplastics into groups according to their physical characteristics.
Polymer composition: Differentiating microplastics based on the kind of polymer they contain.

5. Microplastic Detection Algorithm: To enable thorough microplastic detection, an algorithm is created that combines information from spectral and image data. This program provides a comprehensive understanding of the quantity and existence of microplastics in human tissues by combining the findings from spectral analysis and CNN-based image analysis.

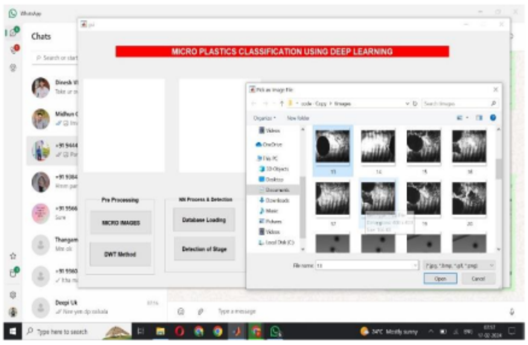

Fig.4 Input images

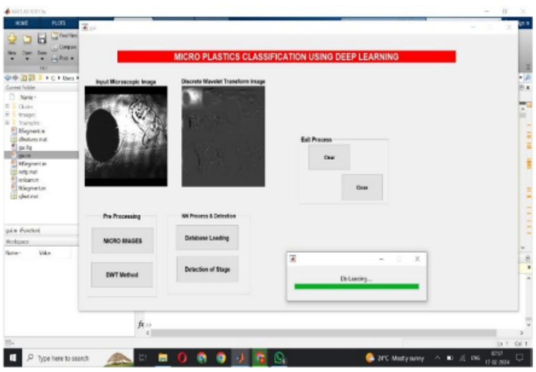

Fig.5 Database loading

Qualities:
1. Automated Analysis: By providing automated microplastic analysis, the technology greatly lowers the requirement for manual intervention. This characteristic improves scalability and efficiency, which makes it ideal for extensive research.

2. Multi-Modal Analysis: A multi-modal analysis technique is made possible by the integration of both spectral and picture data. In order to improve discrimination, this ensures a more thorough understanding of microplastics by gathering both optical and chemical information.

3. Accuracy and Precision: By utilizing deep learning models, the system minimizes human error by identifying microplastics with a high degree of accuracy. This accuracy adds to the detecting system's total accuracy.

4. Health Insights: One unique aspect of the system is its capacity to offer insights into the possible health effects of ingesting microplastics. The system provides useful information for health-related analysis and decision-making by providing comprehensive data on the kinds, amounts, and distributions of microplastics.

5. Real-time Processing: The system is made to process data effectively and in real-time, allowing for prompt analysis and result presentation. This is especially useful in scenarios where making decisions quickly is essential.
Through the integration of various techniques and functionalities, the suggested Deep Learning-Based Detection System endeavors to surmount the constraints of manual examination, providing an advanced and effective resolution for the all-encompassing examination of microplastics within human tissues.

.

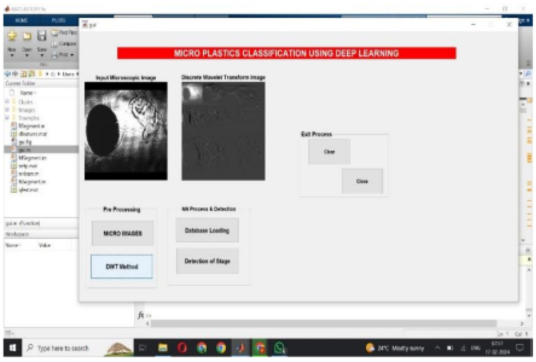

Fig.6 Input image with feature extration

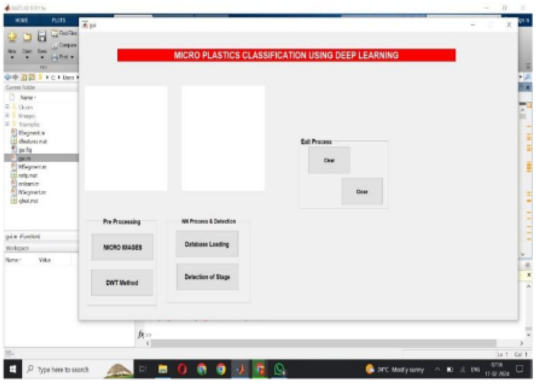

Fig.7 Partial output

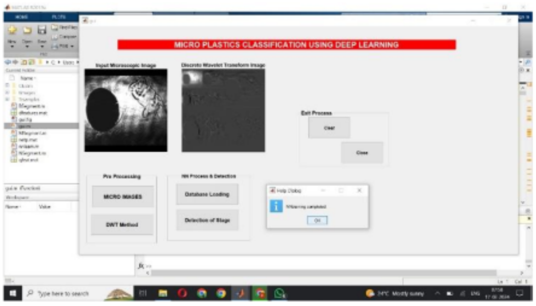

Fig.8 Training completed

Fig.9 Partial output

V. CONCLUSION:

To summarise, this study utilises state-of-the-art deep learning algorithms to automatically identify microplastics in human tissues with the goal of improving our knowledge of their consumption and related health hazards. This study advances a more thorough understanding of the complex interactions between microplastics and the human body by accelerating the analysis process. The use of cutting-edge technology not only represents a significant improvement in productivity but also demonstrates our dedication to addressing the pressing demand for knowledge on the potential health effects of microplastic exposure. In the end, our research adds important knowledge for well-informed policy formulation and decision-making, which advances the larger conversation on environmental and public health.

References

[1] Policy Scenarios for Global Plastics Outlook to 2060 and 2022 [online] Accessible

[2] "Characterization of petroleum-based plastics and their absorbed trace metals from the sediments of the Marina Beach in Chennai, India", Environmental Sciences Europe, vol. 32, no. 1, pp. 110, 2020, [online]; T. Y. Suman, W.-G. Li, S. Alif, V. R. P. Faris, D. J. Amarnath, J.-G. Ma, et al. https://doi.org/10.1186/s12302-020-00388-5 is accessible.

[3] N. Fisheries, NOAA Fisheries (Southeast National), January 2021, [online], Deepwater Horizon 10 Years Later: 10 Questions The website https://www.fisheries.noaa.gov/news/deepwater-horizon-10-years-later-10-questions is currently accessible.

[4]*IUCN*,[online]Available:https://www.iucn.org/resources/issues-brief/marine-plastic-pollution.

[5] In 2018, T. M. Karlsson, L. Arneborg, G. Broström, B. C. Almroth, L. Gipperth, and M. Hassellöv published "The unaccountability case of plastic pellet pollution" in Marine Pollution Bulletin, vol. 129, no. 1, pp. 52–60 [online]. The following is available: 10.1016/j.marpolbul.2018.01.041.

[6] The article "Production use and fate of all plastics ever made" was published online in Science Advances on July 3, 2017, by R. Geyer, J. R. Jambeck, and K. L. Law. The URL https://doi.org/10.1126/sciadv.1700782 is accessible.

[7] In the 38th Aerospace Science Meeting Exhibit, D. C. McCormick presents "Boundary layer separation control with directed synthetic jets" on pages 1-11, available online. The URL http://arc.aiaa.org/doi/abs/10.2514/6.2000-519 is accessible.

[8] Theor. Appl. Mech. Lett., vol. 5, no. 1, pp. 35–38, 2015, [online]; Y. Li, H. Bai, and N. Gao, "Drag of a D-shaped bluff body under small amplitude harmonic actuation" [http://dx.doi.org/10.1016/j.taml.2015.01.005] is the URL accessible.

[9] Environ. Res. Lett., vol. 15, no. 2, pp. 1-32, Feb. 2020; E. van Sebille et al., "The physical oceanography of the transport of floating marine debris".

[10] Sci. Total Environ., vol. 729, Aug. 2020; Y. Xia, X.-M. Xiang, K.-Y. Dong, Y.-Y. Gong, and Z.-J. Li; "Surfactant stealth effect of microplastics in traditional coagulation process observed via 3-D fluorescence imaging".

[11] PO.DAAC CA USA, CYGNSS Level 2 Science Data Record, Version 2.1. Dataset [online], December 2018. The URL https://doi.org/10.5067/CYGNS-L2X21 is accessible.

[12] In December 2017, Zhang H. published "Transport of microplastics in coastal seas" in Estuarine Coastal Shelf Sci., vol. 199, pp. 74-86.

[13] Fourth Edition of the Guidelines for Drinking-Water Quality, With the First and Second Addenda, World Health Organization, Geneva, Switzerland, 2022.

[14] Environ. Sci. Adv., vol. 1, no. 1, pp. 9–29, 2022; P. Roy, A. K. Mohanty, and M. Misra, "Microplastics in ecosystems: Their implications and mitigation pathways".

[15] Environmental Pollution, vol. 292, Jan. 2022; A. Yusuf et al., "Updated review on microplastics in water their occurrence detection measurement environmental pollution and the need for regulatory standards".

RE-2022-212909-plag-report

ORIGINALITY REPORT

13%	11%	9%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.slideshare.net Internet Source	3%
2	R. Prabu, C.Thirumalai Selvan, P. Vijayanand. "Supervision for Obscure Places to Avoid Intrusion using NNSA", 2022 7th International Conference on Communication and Electronics Systems (ICCES), 2022 Publication	1%
3	Submitted to SRM University Student Paper	1%
4	www.ijnrd.org Internet Source	1%
5	mafiadoc.com Internet Source	1%
6	Submitted to University of Gloucestershire Student Paper	1%
7	www.mdpi.com Internet Source	1%

8	Submitted to CITY College, Affiliated Institute of the University of Sheffield Student Paper	1 %
9	Submitted to Saveetha Dental College and Hospital, Chennai Student Paper	1 %
10	media.neliti.com Internet Source	1 %
11	Submitted to Universiti Malaysia Perlis Student Paper	<1 %
12	Maganti Syamala, Seeniappan Kaliappan, Haripriya M P, K.P. Aishwarya, R. Venkatesh, Anuj Raturi. "Performance Analysis of Lightweight Virtualization for Environments with Edge Computing Based on NFV", 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), 2023 Publication	<1 %
13	Submitted to Middlesex University Student Paper	<1 %
14	Swetha P, Mohanram S. "Brain Tumour Segmentation Based on SFCM using Back Propagation Neural Network", International Journal of Innovative Technology and Exploring Engineering, 2019 Publication	<1 %

15	www.ir.juit.ac.in:8080 Internet Source	<1 %
16	dokumen.pub Internet Source	<1 %
17	www.cse.unr.edu Internet Source	<1 %
18	calhoun.nps.edu Internet Source	<1 %
19	C. Senthilkumar, R. K. Gnanamurthy. "A Fuzzy clustering based MRI brain image segmentation using back propagation neural networks", Cluster Computing, 2018 Publication	<1 %

Exclude quotes	On	Exclude matches	Off
Exclude bibliography	On		