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A Computational Approach To Predict The Microplastic Ingestion In The Human Body

Dr.B.Satish Kumar
Department of Mechanical Engineering,
Lendi Institute of Engineering and Technology, Vizianagaram

Gulivindala Anil Kumar
Department of Mechanical Engineering,
Lendi Institute of Engineering and Technology, Vizianagaram

B.Ganesh
Department of Computer Science,
Avanthi Institute of Engineering Technology, Makavarapupalem

RohithKumarr
Department of Mechanical Engineering,
Lendi Institute of Engineering and Technology, Vizianagaram

Sameera
Department of Mechanical Engineering,
Lendi Institute of Engineering and Technology, Vizianagaram

***Abstract*—** Public health is under severe threat due to ingestion of microplastics into human body through various routes. The entry of harmful microplastics into marine environment and ground water increased rate of contamination the plankton growth and food chain. The susceptibility for development of chronic respiratory diseases and deadly cancers is higher and the prediction of their accumulation in human tissues can be helpful to eradicate deadly diseases in the preliminary stages. This, study focuses on human exposure to microplastics, exploring pathways such as ingestion, inhalation, and dermal contact. A novel computational approach is designed to detect and quantify microplastics in biological samples. The primary goal is to advance our understanding of the impact of microplastics on human health and contribute to the development of an automated detection system for comprehensive analysis.

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

I. INTRODUCTION

Legislations are taken many initiatives and imposed strict regulations to the public of various nations for plastic waste management. But the weaker penetration of regulations, lack of motivation in the stakeholders and bottlenecks in the collection, segregation and management process made to settle them at landfills. The reaction of atmospheric moisture, sunlight can lead to leachate formation which have a capability to enter into the groundwater by penetrating different layers of earth. It results as the settling of microplastics into the earth layers and their entry become easy into the food chain with the plankton, microbial growth. The direct ingestion of milli, micro and nanosized plastics have greater susceptibility of creating harmful cancers with the long-term exposure by damaging human tissues, blood cells and affect the next generations by entering into placenta and breast milk.

The strong ability of microplastics to conquest various ecological boundaries make them to enter into terrestrial, aquatic, and atmospheric systems. It is prompted them to

Their widespread distribution and persistence in diverse environmental compartments emphasize the urgency of addressing this issue. Within aquatic ecosystems, microplastics undergo fragmentation and degradation, resulting in the formation of smaller particles that can easily infiltrate the food chain, affecting various marine organisms. Consequently, the repercussions extend to human populations that rely on these marine resources, creating a potential pathway for microplastics to enter the human body.

This study focuses on a crucial dimension of the microplastics conundrum – their presence and potential accumulation in the human body. Human exposure to microplastics occurs through multiple pathways, with ingestion, inhalation, and dermal contact being the primary routes. Of these, ingestion is identified as a significant concern due to the potential for microplastics to accumulate in tissues and organs, raising questions about their long-term health implications. As a result, this research concentrates on the ingestion pathway, aiming to elucidate the extent of microplastics ingestion, their distribution within the human body, and the potential health risks associated with this pervasive exposure.

The decision to focus on the ingestion pathway stems from its prominence in the overall human exposure scenario, driven by dietary habits, contaminated food sources, and the ubiquitous presence of microplastics in the environment. In doing so, we aim to contribute valuable insights that can inform strategies for mitigating the health risks posed by microplastics and pave the way for the development of effective detection and analysis methods. By unraveling the complexities of microplastics in human systems, this study seeks to address a critical gap in our understanding, facilitating informed decision-making and policy formulation to safeguard both environmental and human health.

II. EXISTING SYSTEM

Traditionally, the existence of microplastics is verified through the labor-intensive methods at which the samples are collected from the specific tests and rigorous investigations are performed. It requires the expertise of the human to trace the microplastics existence in various stages such as sample preparation, analysis and interpretation of the data. The challenges are very higher in the traditional process at which the human intelligence and assistance is required at every instant and the time required to attain such skills are critical which depends on the cognitive skills of the worker.

The limitations of these traditional techniques prompted the need of hour for innovative approaches to address the identified shortfalls. The innovative method should produce the accurate result with minimum consumption of resources and time by using the limited data for the detection of microplastics quantity within the human body. Deep learning one of such innovative methods at which the producing result maintains accuracy by automating the overall process compared to labor intensive manual methods.

III. PROPOSED SYSTEM

The proposed system represents a significant leap forward in the field of microplastics analysis by introducing a Deep Learning-Based Detection System. This innovative approach combines cutting-edge deep learning models with advanced techniques in image and spectral analysis to revolutionize the detection and quantification of microplastics in human biological samples. At its core, deep learning models, particularly Convolutional Neural Networks (CNNs), are employed to autonomously analyze microscopic images, allowing for the identification and localization of microplastics within complex biological matrices.

By leveraging the power of deep learning, the system excels in automating the traditionally manual and labor-intensive analysis processes associated with microplastics detection. This automation not only accelerates the analysis workflow but also significantly enhances efficiency by reducing the dependency on human intervention. The integration of image analysis ensures that the system can discern microplastics at a microscopic level, capturing detailed information about their size, shape, and distribution within the biological samples.

Moreover, the inclusion of spectral analysis adds an additional layer of sophistication to the proposed system. This facet allows for the examination of microplastics beyond their visual characteristics, enabling the identification of specific polymers and enhancing the system's overall discriminatory capabilities. The synergistic combination of image and spectral analysis enables a more comprehensive understanding of microplastics in human biological samples.

The overarching goal of this proposed system is to not only streamline the analysis process but also to elevate the accuracy of microplastics detection. Deep learning models, with their ability to learn intricate patterns and features, contribute to a higher degree of precision in identifying microplastics, minimizing the potential for human error. This level of automation and accuracy positions the system as an invaluable tool for large-scale studies, where the efficient processing of substantial datasets is essential for deriving meaningful insights into the extent of microplastics ingestion in the human body.

In essence, the Deep Learning-Based Detection System outlined in this proposal holds the promise of transforming the landscape of microplastics research, providing a sophisticated and efficient solution that addresses the limitations of manual methods. By automating the analysis process, the proposed system not only facilitates a deeper understanding of the health implications of microplastics ingestion but also contributes to the broader discourse on environmental and public health awareness.

DIGITAL IMAGE PROCESSING OVERVIEW:

Digital image processing involves manipulating image data through various techniques, such as noise removal and feature extraction. Objects are identified by interpreting shapes, crucial for applications like recognizing cars or cells. The challenge lies in handling variations in angles and lighting.

Image Digitization:

To process images digitally, they are represented as arrays of pixels. Basic operations include point, local, and global operations, allowing enhancement, restoration, or compression. Image enhancement, like noise smoothing, involves techniques such as median filtering. Contrast manipulation and pseudo-coloring are also common point operations.

Object Class Recognition Challenges:

Recognizing object classes in real-world images is complex due to appearance variations, distortions, and interclass similarity. This paper addresses image classification and object detection using an edge-based approach. It employs simple shape primitives like line segments and ellipses, combining them flexibly to represent object classes. These primitives support abstract reasoning, are scale-normalized, and efficiently match across scales.

Innovative Object Class Recognition:

The paper introduces an approach focusing on edge information and generic shape primitives. It uses combinations of line segments and ellipses to represent complex shapes, adapting flexibly to different object classes. The combinations, termed shape tokens, leverage distinguishing shape, geometric, and structural constraints, providing a novel method for object class recognition.

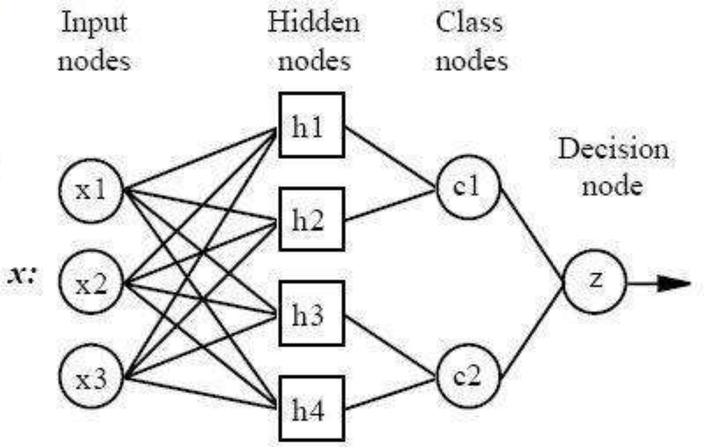
CNN ALGORITHM

CNN refers as convolutive neural networks at which the input is taken as real number of 'x' and the function for the network is taken as 'F' whereas the F'(x) is evaluated broadly in the two phases i.e., 'Feed forward' and 'Back propagation'.

Feed-forward: At the initial stage the input is given to the network and the derivatives are evaluated at each node of the network. The derivatives are stored in the nodes of given primitive network.

Back propagation: The network is allowed to run in backward direction at this step by feeding constants into the output unit. The incoming information to node is added and the result is multiplied by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x.

Architecture of a CNN.



All CNN networks have four layers:

1.Input layer — This layer consists of various neurons at which each predictor variable is assigned with own neuron whereas N-1 neurons are allocated for the variables of different categories. Here 'N' refers as the number of categories and the range of values are standardized in the input neuron by deduction of median and dividing the interquartile range. Each neuron in the hidden layer then receives the values from the input neuron.

2.Hidden layer —

This layer consists of various neurons at which one is assigned for one case in the training data set. Along with the target value, the neuron preserves the values of predictor variable of each case. After calculating the Euclidean distance of the test case, the hidden neuron extracts the sigma values to apply the RBF kernel function. The distance is calculated from the center point of the neuron which is assigned to ‘x’ vector of the input values from the input layer. The produced resultant value is received by the neurons in the pattern layer.

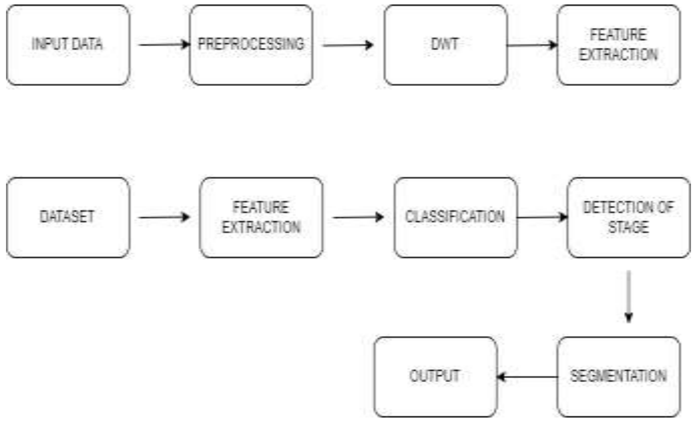
3.Pattern layer / Summation layer —
The structure of pattern layer varies significantly in CNN and GRNN networks. The existence of pattern neuron for every possible category of the target variable can be observed in the CNN networks. The hidden neurons retain the true target category of the existing training cases and the weighted values existed in hidden neuron is directly related to the pattern neuron. The values of each classes are summed up over the pattern neuron and it is solely belong to the weighted voted for the class.

4.Decision layer — The weighted votes are collected from the target categories and those were stored in the pattern layer. These values are evaluated further to find out the largest vote in the pattern layer. The target category is designed to exhibit the largest vote from the assigned values at the hidden layer.

ALGORITHM:
The Convolutional neuralalgorithm is used to compute the necessary corrections, after choosing the weights of the network randomly. The algorithm can be decomposed in the following four steps:

i) Feed-forward computation
ii) Convolutional neural to the output layer
iii) Convolutional neural to the hidden layer
iv) Weight updates
V) Block Diagram (SOFTWARE)

Block Diagram



1. Data Acquisition:
At the forefront of the process is the collection of human tissue samples, a critical step that may involve procedures such as biopsies or other medical interventions. These samples serve as the foundation for understanding the presence and distribution of microplastics within the human body. Ensuring the integrity and representativeness of the collected samples is essential for the reliability of subsequent analyses.

2. Pre-processing:
Pre-processing Steps: In the block diagram outlined in the project, the grayscale filter is applied during the pre-processing stage. This step involves noise reduction, contrast enhancement, and image segmentation to prepare the grayscale images for subsequent analysis. By incorporating the grayscale filter at this stage, the system ensures that the input data is optimized for the deep learning model, facilitating more accurate and efficient microplastics detection. In essence, the utilization of a grayscale filter in the proposed system contributes to the overall success of the microplastics analysis by simplifying data, improving contrast, and aligning with the capabilities of deep learning models. This strategic integration enhances the accuracy and efficiency of the automated detection system, addressing the challenges associated with manual and labor-intensive methods in the existing system.

3. Image Analysis:
In the image analysis module, sophisticated deep learning models, particularly Convolutional Neural Networks (CNNs), are applied to the microscopic images. The primary objective is to detect and localize microplastics within the

complex biological samples. CNNs excel in learning hierarchical features from images, enabling them to discern subtle patterns associated with microplastics, such as their size, shape, and spatial distribution. In the image analysis module, a 6-layer Convolutional Neural Network (CNN) is employed for microplastics detection in biological samples:

i)Input Layer:

Grayscale-filtered microscopic images serve as input, providing the foundation for subsequent analysis.

ii)Convolutional Layer:

Utilizes filters to learn hierarchical features, capturing microplastics-related patterns like size, shape, and spatial distribution.

iii)Activation Layer:

Introduces non-linearities (e.g., ReLU) to enhance the network's ability to model complex relationships within the data.

iv)Pooling Layer:

Downsamples learned features, reducing computational load and focusing on critical information for efficient analysis.

v)Fully Connected Layer:Connects neurons for comprehensive processing of extracted features, facilitating intricate analysis of microplastics characteristics.

vi)Output Layer:

Produces precise results for microplastics detection and localization, offering insights into size, shape, and distribution.

4. Classification:

Following the detection phase, the classification module categorizes the identified microplastics into different groups or types based on various attributes. This may include classifying them according to size, shape, or polymer composition. The classification step adds a layer of granularity to the analysis, providing a more nuanced understanding of the diverse nature of microplastics present in the human tissues.

5. Microplastic Detection:

The core of the system lies in the microplastic detection module, where deep learning models perform intricate analyses on both the images and spectral data. By combining information from different modalities, the system gains a comprehensive perspective on the presence and quantity of microplastics within the human tissues. This multi-modal approach enhances the robustness of the detection system.

6. Results and Insights:

The culmination of the process leads to the presentation of results and insights derived from microplastic detection. These findings, which include details about the types, quantities, and distributions of microplastics, along with insights into potential health implications, are presented to researchers and healthcare professionals. This step facilitates further analysis and decision-making, contributing to the ongoing discourse on environmental and public health awareness.

The outlined process employs a systematic approach, leveraging deep learning and advanced analytical techniques, to comprehensively study microplastics in human tissues. Each module plays a pivotal role in refining and enriching the understanding of microplastic ingestion, contributing valuable insights to the broader field of environmental and human health research.

ALGORITHM FLOW:

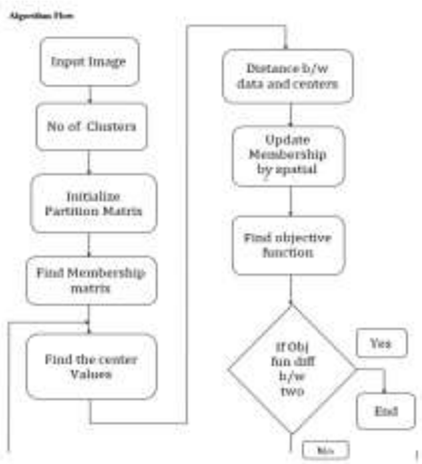


Figure1

Initialize the Fuzzy Weights.

The user is facilitated to initialize the weights in the random fashion by using the feature vectors for attaining effective comparison over the FCM and FCFM. If the user prefers the initialization of weights through the feature vectors, it assigns the K_{init} (user-given) to prototypes. The weights are computed by equation (4) with the successful initialization and assignment of feature vectors.

Standardize the Weights over Q.

The possibility of converging at local optima is higher during the FCM iteration. Because the centers of the computed clusters can get closer with the increase of number of iterations. The rapid convergence at local optima is avoided by grouping the partial clusters into the one large cluster by using the equation (5) before standardizing the weights over Q.

$$w[q,k] = (w[q,k] - w_{min})/(w_{max} - w_{min}) \quad (5)$$

Here w_{max}, w_{min} represents for the maximum or minimum weights over the weights of all feature vectors for the particular class prototype.

Eliminating Empty Clusters.

Elimination of the empty clusters immediate to the fuzzy clustering loop is essential to avoid the excessive time and memory consumption.

Empty cluster elimination usually performed out the fuzzy clustering loop and it appears before modification of XB validity computation. If the elimination is not performed, the distance of any pair of empty clusters can be minimized as like as the protype pair by using equation (8). It is essentially to ensure that the elimination of empty clusters only performed while preserving the non-empty clusters. The pass ‘0’ strategy is applied to the proposing model to preserved the small valued clusters. Following the fuzzy c-means iteration, Step 9 is allowed to determine the cluster centres and the modified Xie-Beni clustering validity κ for comparison and to select the best outcome:

The Xie-Beni validity is a product of compactness and separation measures [10]. The compactness-to-separation ratio ν is defined by Equation (6).

$\nu = \{(1/K)\sum_{(k=1,K)}\sigma_k^2\}/D_{min}^2$

$\sigma_k^2 = \sum_{(q=1,Q)} w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2$

D_{min} is the minimum distance between the cluster centers.

The Modified Xie-Beni validity κ is defined as

$\kappa = D_{min}^2 / \{\sum_{(k=1,K)}\sigma_k^2\}$

The variance of each cluster is calculated by summing over only the members of each cluster rather than over all Q for each cluster, which contrasts with the original Xie-Beni validity measure.

$\sigma_k^2 = \sum_{\{q:\, q \text{ is in cluster } k\}} w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2$

The spatial function is included into membership function as given in Equation

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

DWT (Discrete Wavelet Transform):

Analyzing and extracting features from microplastics data in the project.

Segmentation:

Application: Isolating microplastics in biological samples for precise analysis.

GLCM (Gray-Level Co-occurrence Matrix) Algorithm:

Extracts texture features, providing insights into microplastics' characteristics.

CNN (Convolutional Neural Network):

Analyzing microscopic images and detecting microplastics by learning hierarchical features.

Software Requirements:

i)MATLAB 2019:

Central computing environment for data processing and algorithm implementation.

ii)Image Processing Toolbox:

Facilitates image analysis, manipulation, and enhancement for accurate microplastics detection.

iii)Deep Learning Toolbox:

Enables the implementation of Convolutional Neural Networks (CNNs) for intricate pattern learning.

iv)Data Acquisition Toolbox:

Efficiently acquires, analyzes, and visualizes data from various sources.

IV. Methods:

1. Convolutional Neural Networks (CNNs):

CNNs serve as the primary deep learning architecture for image analysis in microplastics detection. These neural networks are adept at automatically learning hierarchical features from images, making them well-suited for discerning subtle patterns associated with microplastics, including size, shape, and spatial distribution. The convolutional layers enable the network to capture local patterns, while fully connected layers aggregate this information for precise identification.

2. Image Pre-processing:

Pre-processing techniques are applied to enhance the quality of captured microscopic images. This includes:

Noise Reduction: Employing filters and algorithms to reduce noise artifacts.

Contrast Enhancement: Adjusting image contrast for improved visibility of microplastics.

Image Segmentation:Dividing the image into segments to facilitate more targeted analysis.

3. Spectral Analysis:

Spectral analysis involves the examination of microplastics beyond their visual characteristics. This can include techniques such as Fourier Transform Infrared Spectroscopy (FTIR) or Raman Spectroscopy to identify specific polymers constituting microplastics. Spectral data is crucial for an additional layer of discrimination in the classification process.

4. Classification Models:

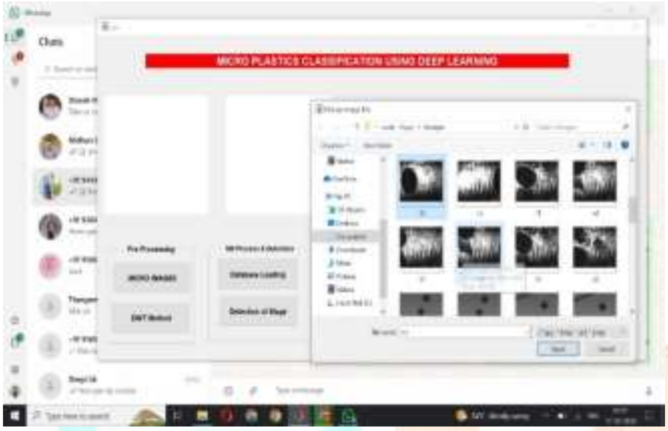
Classification models are implemented to categorize detected microplastics based on various attributes, including:

ize:Grouping microplastics according to their dimensions.

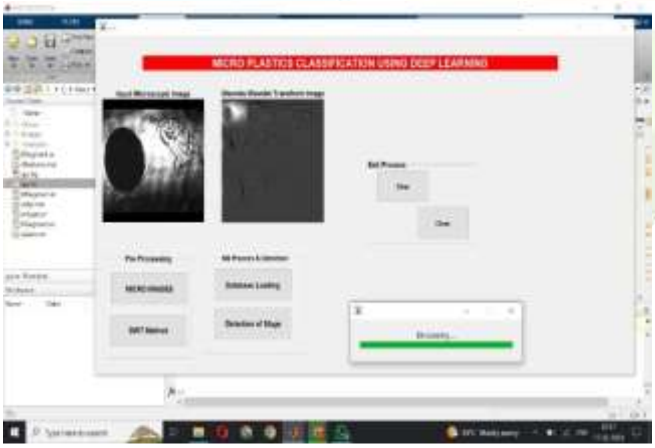
Shape:Categorizing microplastics based on their morphological features.

Polymer Composition: Distinguishing microplastics by the type of polymer they are composed of.

5. Microplastic Detection Algorithm:
An algorithm is developed to integrate information from both image and spectral data for comprehensive microplastic detection. This algorithm combines the results from the CNN-based image analysis and spectral analysis, providing a holistic understanding of the presence and quantity of microplastics in human tissues.



Input images



Database loading

Features:
1. Automated Analysis:
The system offers automated analysis of microplastics, significantly reducing the need for manual intervention. This feature enhances efficiency and scalability, making it well-suited for large-scale studies.

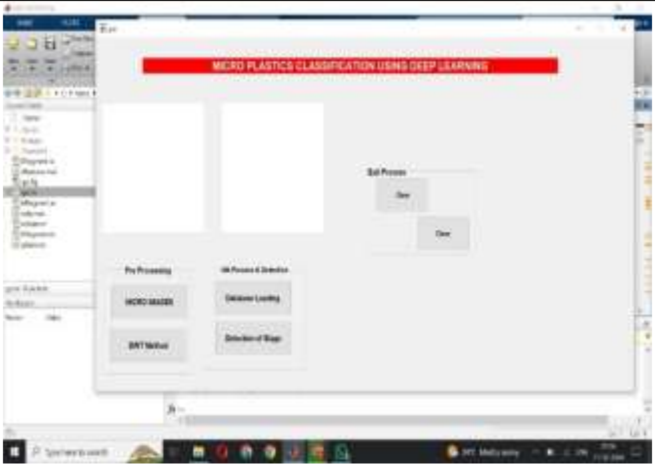
2. Multi-Modal Analysis:
The integration of both image and spectral data allows for a multi-modal analysis approach. This ensures a more comprehensive understanding of microplastics, capturing both visual and chemical information for improved discrimination.

3. Precision and Accuracy:
Leveraging deep learning models, the system achieves a high degree of precision in microplastics identification, minimizing human error. This precision contributes to the overall accuracy of the detection system.

4. Health Insights:
The system's capability to provide insights into the potential health implications of microplastics ingestion is a distinctive feature. By presenting detailed information about the types, quantities, and distributions of microplastics, the system contributes valuable data for health-related analyses and decision-making.

5. Real-time Processing:
The system is designed for efficient real-time processing of data, enabling timely analysis and presentation of results. This is especially valuable for applications where quick decision-making is crucial.
By incorporating these methods and features, the proposed Deep Learning-Based Detection System strives to overcome the limitations of manual analysis, offering a sophisticated and efficient solution for the comprehensive study of microplastics in human tissues.

Input image with feature extration



Partial output

Training completed

Partial output

V. Conclusion

An innovative method is proposed to quantify the existence of microplastics in the human body through deep learning techniques in this research. The susceptibility of getting cancers and possible risk to human with the damage of tissues from the existence of microplastics at various locations of the human body is investigated through the deep learning technique in this research. Although, the primary goal is to advance our understanding of the impact of microplastics on human health, it highlights the current need of hour for the innovative methods to avoid health risks in the low literacy rate countries and areas at where the medical awareness is significantly low. At overall, this research prioritizes the environmental and public health by contributing valuable knowledge for policy formulation and decision making.

References

[1] *Global Plastics Outlook: Policy Scenarios to 2060*, 2022, [online] Available

[2] T. Y. Suman, W.-G. Li, S. Alif, V. R. P. Faris, D. J. Amarnath, J.-G. Ma, et al., "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] Available: https://doi.org/10.1186/s12302-020-00388-5.

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

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

[5] T. M. Karlsson, L. Arneborg, G. Broström, B. C. Almroth, L. Gipperth and M. Hassellöv, "The unaccountability case of plastic pellet pollution", *Marine Pollution Bulletin*, vol. 129, no. 1, pp. 52-60, 2018, [online] Available: https://doi.org/10.1016/j.marpolbul.2018.01.041.

[6] R. Geyer, J. R. Jambeck and K. L. Law, "Production use and fate of all plastics ever made", *Science Advances*, vol. 3, no. 7, pp. e1700782, 2017, [online] Available: https://doi.org/10.1126/sciadv.1700782.

[7] D. C. McCormick, "Boundary layer separation control with directed synthetic jets", *Proc. 38th Aerospace Sci. Meeting Exhibit*, pp. 1-11, [online] Available: http://arc.aiaa.org/doi/abs/10.2514/6.2000-519.

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

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

[10] 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", *Sci. Total Environ.*, vol. 729, Aug. 2020.

[11] *CYGNSS Level 2 Science Data Record Version 2.1. Ver. 2.1. PO.DAAC CA USA. Dataset*, Dec. 2018, [online] Available: https://doi.org/10.5067/CYGNS-L2X21.

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

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

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

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