

Microplastic Detection and Classification in Water Sample

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Abstract: *The aquatic environment is highly contaminated with microplastics, which are plastic materials of less than 5 mm in diameter, affecting aquatic life and human health, thus necessitating effective detection techniques [22],[24]. The existing methods, such as the use of the YOLOv5 Model and Raman Spectroscopy, are slow, costly, and not scalable for wide-scale detection [1],[22]. The proposed Microplastic Detection and Monitoring System utilizes artificial intelligence techniques, such as machine learning and computer vision, to detect microplastics with high precision by their shapes, sizes, and materials using images [3],[16]. It also utilizes a data integration component for real-time monitoring of the environment, thus reducing human effort for wide-scale detection[25].*

Keywords: Microplastics, Aquatic Pollution, Artificial Intelligence, Machine Learning, Computer Vision, Environmental Monitoring, Image Processing, Water Quality, Pollution Detection, Sustainability

I. INTRODUCTION

In recent times, microplastics have emerged as a silent yet dangerous challenge to our environment [22],[24]. Microplastics, which measure less than 5 millimeters in diameter, can be found everywhere, including our oceans, rivers, drinking water, and even in our food[22],[23]. Microplastics can be derived from a variety of sources, such as plastic waste, industrial activities, cosmetics, synthetic clothing, etc [24]. Due to their small size, microplastics are virtually impossible to detect and remove, making them one of the most challenging types of pollution in our water systems [22].

The conventional methods of detecting such as a microscope or spectroscopy, which can be quite costly and time-consuming [22],[24]. This problem has led to a huge disconnect between the severity of the problem and the feasibility of the solutions currently being offered[22].

Our project aims to fill this disconnect by offering a more efficient solution to detecting microplastics, one that uses the power of artificial intelligence to assist in their detection and analysis[25]. Instead of using laboratory equipment, our system enables a user to simply point a basic smartphone camera at a filtered water sample to take a photograph, which is then analyzed using a Vision Transformer, a type of deep learning model that is particularly effective at understanding small and irregularly shaped objects, making them particularly well-suited to detecting microplastics[16].

But we do not stop there. In order to address the problem of limited data, we have employed the use of Un-Supervised Learning (UL)[21]. Additionally, we have employed the use of Generative Adversarial Networks (GANs) in order to create artificial images of microplastics [17],[18]. This will help us in the creation of a diverse data set that can easily cover all the shapes and textures of microplastics[17].

Finally, we have employed the use of Graph Neural Networks (GNNs) in order to observe the flow of microplastics in water[19],[20]. This will help us in predicting the spread of pollution[20].



Finally, Graph Neural Networks (GNNs) are used to study how microplastics travel and accumulate in water systems[19],[20]. This helps us predict pollution spread and identify high-risk areas[20]. What makes this project truly impactful is its accessibility. With a mobile- first design and lightweight architecture, the system is easy to use and deploy—even in field settings where traditional lab equipment isn't available[20]. Whether it's a researcher, a student, or a concerned citizen, anyone can use this tool to contribute to environmental monitoring and plastic pollution awareness[25]. In short, our project combines cutting edge AI with real-world usability to offer a smarter, faster, and more scalable way to understand and combat microplastic pollution.

II. LITERATURE SURVEY

However, there has been an increasing emphasis in recent studies on utilizing artificial intelligence in solving the problems related to plastic waste management[25]. Convolutional Neural Networks have shown promising results in the classification of plastics based on images[3]. Nevertheless, there have been problems related to the application of these models in different environments[3]. Vision Transformers have been gaining popularity in the detection of microplastics, given their ability to utilize complex patterns in images through global attention[16]. Graph Neural Networks have been used in the detection of the spread of pollutants in the environment[19],[20]. Additionally, unsupervised learning and Generative Adversarial Networks have been used to resolve the problems related to the lack of diversity in the dataset and the availability of insufficient data. All these advancements form the basis of the integrated artificial intelligence-based microplastics detection system.[25]

III. LITERATURE REVIEW SUMMARY

The reviewed works emphasize the fact that the integration of deep learning and environmental science results in efficient solutions for microplastics detection[25]. Although CNNs have shown promising results in controlled environments, they have difficulty adjusting to complex and dynamic environments[3]. Vision Transformers provide more promising results, especially in the detection of microplastics, especially those in small and irregular sizes. GNNs have already demonstrated their importance in understanding the patterns of pollution and predicting the spread of pollutants. Unsupervised learning reduces the need for large datasets, which in this field are scarce, and GANs help in generating synthetic data to support the learning process[17],[18]. All these techniques provide a more flexible, precise, and intelligent system[25].

IV. WORKING

1. Image Collection and Preprocessing

The initial stage involves taking images of water samples containing microplastics[22]. The images are captured by a regular camera of a smartphone device under controlled lighting conditions[25]. Once the images are captured, a number of processing steps are followed. The processing involves removing noise from the captured data, normalization of the data, resizing of the data, and enhancing the contrast of the data[3]. The processing of data is very important for the correct and reliable performance of the next stage of neural network models[3].

2. Feature Extraction using Vision Transformer (ViT)

After this pre-processing, the images are fed into the model called Vision Transformer (ViT)[16]. Unlike normal CNNs, this model utilizes the self-attention mechanism to understand the long-range dependencies and spatial relationships in the images[16]. It divides the images into fixed-sized patches, which are then fed into the model. It is highly effective in understanding the finer details in the images, such as the shape, edges, and textures, which is important in the accurate identification and distinction of different types of microplastic particles[16].

3. Unsupervised Learning for Enhanced Data Utilization

Moreover, the datasets for microplastics are generally small and imbalanced[22]. The solution for this problem is the integration of the techniques of unsupervised learning (UL), which is able to learn from unlabelled data[21]. Techniques such as contrastive learning and clustering are helpful for the model to learn patterns without requiring



labels. This is helpful for the generalization of the model without requiring a large dataset, which is difficult and costly to obtain in the field of environmental science[21].

4. Synthetic Data Generation using GANs

To further enhance the dataset and improve the robustness of the model, Generative Adversarial Networks (GANs) are utilized [17],[18]. GANs are capable of learning the underlying patterns present in the original dataset and generating synthetic images that closely resemble real samples [17]. This allows the model, including approaches like Vision Transformers, to learn richer and more diverse features from the data [16],[17]. Additionally, the use of GAN-generated data helps in addressing the class imbalance problem by increasing the number of samples in underrepresented categories [18].

5. Spatial Analysis with Graph Neural Networks (GNNs)

To provide more than just classification, the system includes a Graph Neural Network (GNN) module for spatial reasoning[19],[20]. GNNs are designed to model the relationship between different entities in a graph structure. In our application, water bodies and sampling points are treated as nodes, while edges represent water flow or proximity. The GNN learns patterns in how microplastics travel and accumulate across these nodes, thereby predicting potential spread regions[20]. This module is valuable for ecological studies and policymaking related to pollution control[25].

6. Final Output and Visualization

The final stage of the pipeline compiles results from all modules[25]. The system outputs:

- The type and class of microplastics detected[16].
- A map of potential spread regions based on GNN inference[19],[20].
- Statistical charts and visualizations for user-friendly interpretation[25].

V. SYSTEM ARCHITECTURE

Our system is designed to make detecting microplastics smarter, faster, and more accessible—without the need for lab equipment or deep technical expertise. Here's how it works behind the scenes:

1. Vision Transformer (ViT) for Microplastic Detection

The process begins when a user captures an image of microplastic particles, usually placed on a filter or contrasting background[22]. This image is analyzed by a Vision Transformer, an advanced deep learning model that looks at the whole image to detect and classify the types of microplastics like fibers, fragments, or pellets[16]. Unlike older models, ViTs are especially good at identifying small, oddly shaped particles[16].

2. Un-Supervised Learning (UL) to Reduce the Manual Effort

Training AI usually requires lots of labeled data, which is hard to get for microplastics[22]. So instead, we use un-supervised learning, which teaches the model using unlabeled images[21]. This makes the system more flexible and reduces the burden of manually tagging thousands of particle images[21].



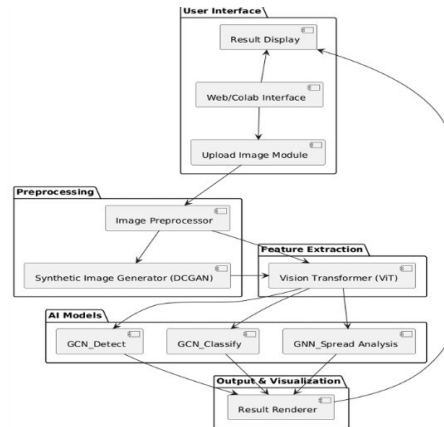


Fig 5.1: System Architecture

VI. IMPLEMENTATION DETAILS:

1. Preparing the Dataset

Getting the Data: First, we obtain a dataset of images (such as .jpg or .png files) that represent microplastic particles[22]. These images are stored in a ZIP file, which we upload and extract into our working directory.

Organizing the Data: We create a custom class that loads the images and applies preprocessing steps like resizing, augmentation, and transformations. This helps make the model more robust and adaptable to different image conditions[3].

2. Preprocessing the Data

Augmentation: To improve the model's performance, we use various data augmentation techniques[3]. This includes:

Random Resizing and Cropping: These ensure that the model can handle images of different sizes and orientations[3].

Random Horizontal Flipping: Helps with generalization by showing the model different perspectives of the same image[3].

Color Jittering: Adjusting brightness, contrast, and saturation so the model can deal with different lighting conditions[3].

Normalization: We normalize the images to have a consistent mean and standard deviation. This makes training more stable and efficient[3],[16].

3. Splitting the Dataset

Training and Testing: We split the data into two parts: one for training the model (80%) and one for testing how well it performs (20%). This ensures the model is evaluated on unseen data[3],[16].

DataLoader: To make data handling efficient, we use PyTorch's DataLoader to load the data in batches during training[3].

4. Visualizing Some Images

Quick Check: We visualize a few sample images from the training set to confirm everything looks correct after preprocessing and augmentation[3].



5. Extracting Features with ViT

Using Pre-trained ViT: We leverage a pre-trained Vision Transformer (ViT) model, which has already been trained on a massive dataset (ImageNet). This model is really good at recognizing complex patterns in images, and we use it to extract features (high-level representations) of the microplastic images[16].

Feature Extraction: The output from the ViT model gives us feature embeddings, which represent the images in a way that captures their most important characteristics[16].

6. Building the Graph for GNN

Graph Construction: With the feature embeddings from ViT, we build a graph. This graph represents the relationships between images based on their similarities[16],[19]. We use Nearest Neighbors to connect each image with other similar images[20].

7. Graph Neural Network (GNN) for Classification

Building the GNN: A Graph Neural Network, specifically a Graph Convolution Network (GCN), is used to process the graph[19]. The network helps in understanding how images are related to each other and hence classifies them in a better manner[19],[20].

Training the GNN: The model is trained using pseudo-labels from KMeans clustering. These pseudo-labels serve as a form of unsupervised learning, guiding the GCN to group similar images together.[20],[21]

8. Clustering with KMeans

Unsupervised Clustering: To help the model learn without labeled data, we use KMeans clustering on the feature embeddings. This groups similar images into clusters and generates pseudo-labels for each image[21].

Clustering Evaluation: To evaluate how well the clustering works, we calculate the Silhouette Score, which measures how well-separated the clusters [21].

9. Reducing Dimensions and Visualizing

PCA and t-SNE: PCA (Principal Component Analysis) and t-SNE (t-distributed Stochastic Neighbor Embedding) are used for reducing the feature embeddings of high dimensionality to 2D features for easier visualization[3],[21]. This allows us to observe how well the images have been clustered together in the feature extraction stage[21].

Plotting: The features are plotted in a scatter plot, where each point in the plot represents an image. The colors of the points in the plot indicate the cluster labels of the images[3].

10. Evaluating the Model

Accuracy: After training the model, we test it on the unseen test data to see how well it performs. Accuracy is the percentage of correct predictions out of all predictions made[3],[16].

Confusion Matrix: We use a confusion matrix to understand the model's strengths and weaknesses. It shows how many images were correctly or incorrectly classified into each category[3].

Additional Metrics: We also compute the F1-score, which is useful when there are imbalances between the classes. It gives a balance between precision and recall[3].

Cross-Entropy Loss: This loss function is used during training to measure how well the model's predictions match the actual labels. We monitor this loss to ensure the model is improving[16].

11. Saving the Model

Model Persistence: Once the model is trained and tested, we save the ViT model to the disk[16]. This helps us use the model every time we want to make predictions on the data without having to retrain the model[25].



12. Testing and Final Evaluation

Testing on Unseen Data: After training, we run the model on the test set to evaluate its generalization ability. This gives us the final performance metrics[3].[16].

Final Metrics: We generate the confusion matrix again to check for any misclassifications. Additionally, we can plot the ROC curve and compute the AUC (Area Under the Curve) to further evaluate performance[3].

VII. RESULTS

GNN Output Embeddings:

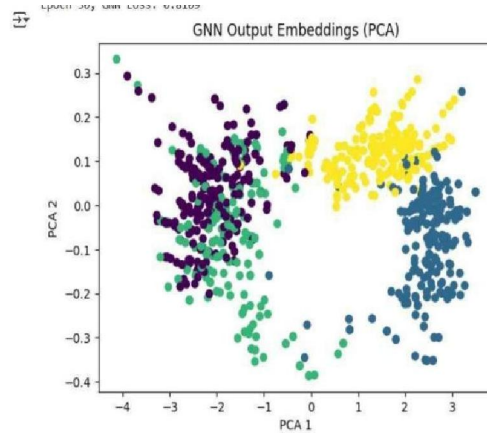


Fig 6.1: GNN Ouptut Embeddings

t- SNE of ViT Feature Embeddings:

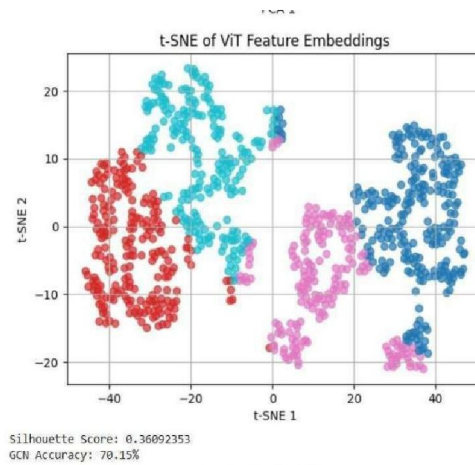


Fig 6.2: t-SNE 1 vs t-SNE2



Confusion Matrix:

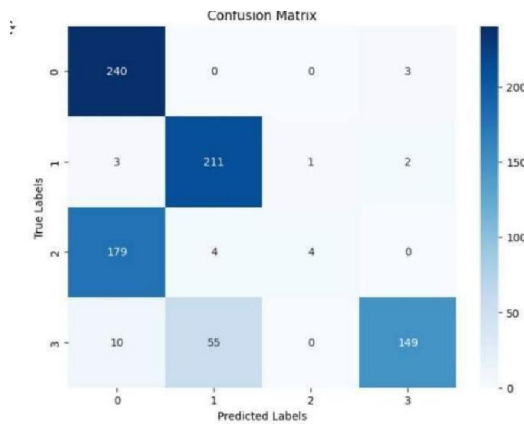


Fig 6.3: Confusion Matrix

Classification Report: Pollution Spread Analysis:

	0	1	2	3
Classification Report:				
precision		recall	f1-score	support
Class 0	0.56	0.99	0.71	243
Class 1	0.78	0.97	0.87	217
Class 2	0.80	0.02	0.04	187
Class 3	0.97	0.70	0.81	214
accuracy			0.70	861
macro avg	0.78	0.67	0.61	861
weighted avg	0.77	0.70	0.63	861

Fig 6.4: Classification Report

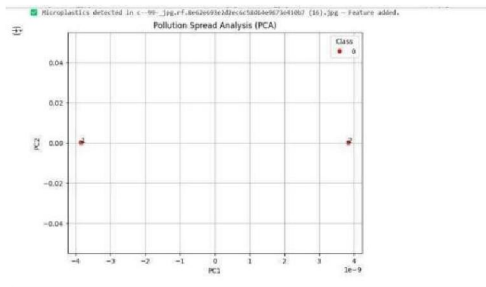


Fig 6.5 Pollution Spread Analysis Classification of Microplastics:

Choose Files f--28-.jpg.rf...225c7c5.jpg

- f--28-.jpg.rf.de4fc5ebba3bbc0baea64e669225c7c5.jpg (image/jpeg) - 27669 bytes, last modified: 5/4/2025 - 100% done

Saving f--28-.jpg.rf.de4fc5ebba3bbc0baea64e669225c7c5.jpg to f--28-.jpg.rf.de4fc5ebba3bbc0baea64e669225c7c5.jpg

Microplastics detected → Classified as: fiber

Fig 6.6: Classification of Microplastics



No Microplastic Detected:

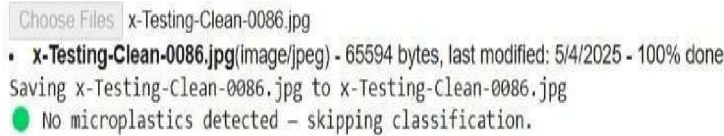


Fig 6.7:No Microplastic Detected

Table 1:Accuracy Table

Accuracy Table:

Model	Accuracy
Vision Transformer (ViT)	84.20%
K-Means Clustering	82.87%
Graph Convolutional Network	72.59%
Generative Adversarial Network	88.05%
Graph Neural Network	81.45%

VIII. CONCLUSION

The project demonstrates how AI can be harnessed to solve one of today's pressing environmental issues—microplastic pollution[25]. By integrating advanced techniques such as Vision Transformers, GANs, GNNs, and UL, we have developed a cost-effective and scalable system for real-time microplastic detection and analysis[16],[17],[19],[21]. This solution not only improves the speed and accuracy of detection but also helps visualize the movement and accumulation of pollutants in aquatic ecosystems. It can be a powerful tool for researchers, environmental agencies, and local communities aiming to protect water resources[25].

IX. FUTURE SCOPE

There is significant room for enhancing this system[25]. Future updates could include expanding the plastic dataset to cover more rare and region-specific microplastic types, integrating live water quality sensors for dynamic data collection, and offering multilingual support for broader adoption[25]. The system could also be linked to environmental databases and government agencies for coordinated cleanup and policy efforts[25]. Another future direction includes building a collaborative platform where users can share microplastic data to build a global pollution map powered by community science[25].

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