Initial study on applicability of thermal imaging for microplastics identification in aquatic medium

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Owing to plastic's durability, plastic waste management is challenging. The current issue is that millions of tonnes of plastic end up in the ocean, possibly resulting in microplastic pollution and becoming the most prevalent underwater contaminant. Efficient identification of microplastic pollution is a scientific challenge because as the size of the particles decreases, it becomes more difficult to recognize and detect them. In this work, we demonstrate a deep learning-based approach for microplastics identification. The dataset is acquired using the thermal imaging technique. Data collection is followed by a data pre-processing step and finally, a classification step. The reported best accuracy, 97.42%, is achieved using the CNN model. The proposed approach allows for the deployment of increasingly diversified models as deep-learning models are still progressing.

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1. Introduction

Plastic production had exponential growth, and over the past half-century, it skyrocketed to 311 megatonnes in 2014 from merely 15 megatonnes in 1964. This trend is anticipated to continue doubling over the next twenty-year period as the use of plastic is expanding in many applications. On the other end the AI and deep learning concepts have been used for many applications [1,2]. As one of the greatest threats to humanity, plastic pollution is now pervasive and found in the air, on land, and in the ocean. Most plastic debris eventually find its way into the ocean through lakes and rivers, where it can linger for years [3].

According to statistics, 12 million tonnes of plastic litter enters the ocean yearly, and the UN alludes to this as a "planetary crisis." And lately, the emphasis on microplastic as a potential pollutant has risen globally, leading to this new scope of research. Microplastics are defined as synthetic solid particles of size spanning between 1 μm and 5 mm with regular or irregular shapes. Its manufacturing origin can be either primary or secondary. Microbeads in personal care items and cosmetics are an example of primary microplastics that are made intentionally by humans. Decomposition of larger plastic materials like tires, bags, and other items due to various environmental causes, results in secondary microplastics [4-6].

To establish the groundwork for a deeper comprehension of distribution, abundance, and risks associated with microplastics, a bibliometric analysis was carried out based on 1138 related articles on the Web of Science. It reports that the chemical makeup of microplastics and the contaminants that adhere to them can cause negative impacts on marine species like reducing food intake, inhibiting growth and reproduction, and disrupting physiological processes (e.g., cell division, hormone secretion, immunity) that might lead to starvation and death. Thus, microplastics have the potential for bioaccumulation and biomagnification [7,8].

Microplastics in water behave differently based on their density. Dense microplastics sink and cluster near the source, while lighter microplastics float and get carried away. However, the net buoyancy can be impacted by a few processes (such as biofilms, gas bubbles, and ageing), causing microplastics to settle in the sediments [9].

The efficient identification and quantification of microplastic pollution is a scientific hurdle since it gets harder to distinguish and identify smaller particles. Most of the research focuses on the in-situ detection of microplastics in the air, while only a few focus on the challenging water environment, due to constraints like light absorption and scattering. Many techniques are explored and investigated for microplastic detection. Recently, optoelectronic techniques were used for the plastics identification and water quality parameters estimation [10-12]. But currently, there are hardly a few quick, standardized, and straightforward analytical techniques that can reliably identify microplastics in actual water in various environmental matrices outside of laboratories.

Given these antecedents, the goal of this research is to design a detailed algorithm that can recognize and classify the lighter microplastics that float at the surface level. More specifically, the idea put forth here intends to leverage computer vision and deep learning methods to accelerate the classification of microplastics at surface water. The paper's findings can be summed up as: Identification of microplastics using thermal imaging technique and assessing suitable deep-learning algorithms.

2. Related work

There is no one standard solution to identify microplastics, and visual inspection is almost always the most common method for identifying and quantifying microplastics, even if tracked by chemical analysis. In visual inspection, particles are categorized as plastic based on physical characteristics, either directly observed or observed under a stereoscope or microscope. In these methods, microplastics must be isolated and treated individually from samples such as water, sediment, or organisms. Thus, the identification phase requires a time-consuming measure of highly competent researchers [13].

According to the literature, spectroscopic methods like Fourier transforms infrared (FTIR) and Raman spectroscopy are used most frequently to identify microplastics [14, 15]. These techniques are fast and reliable for identifying and distinguishing various microplastic types. While non-destructive, the sample preparation involving microplastic extraction from the environment may be potentially detrimental to the sample due to the physical detachment from the backdrop.

Other analytical techniques, such as scanning electron microscopy (SEM), scanning electron microscopy–energy dispersive X-ray spectroscopy (SEM-EDS), and environmental scanning electron microscopy-energy dispersive X-ray spectroscopy (ESEM-EDS) have also been used to characterize microplastics [11]. However, these techniques can be time-consuming, expensive, and potentially detrimental to the sample during sample preparation.

Thermal analysis is an alternative approach gaining popularity for microplastic identification. It involves identifying the polymer based on its degradation products. This methodology includes various techniques such as thermogravimetry (TGA), TGA coupled with mass spectrometry (TGA-MS), TGA-thermal desorption-gas chromatography-mass spectrometry (TGA-TD-GC-MS), pyrolysis gas chromatography-mass spectrometry (py-GC-MS), and differential scanning calorimetry (DSC). These thermal analysis techniques equip beneficial insights into microplastic composition and properties. But they are destructive and may have limitations in sensitivity, accessibility, and practicality [16].

Given the limitations of these techniques, there is a great need for a new approach to facilitate easy and efficient identification of microplastics. Also, as anticipated in the introduction, microplastic detection at the water surface is challenging. Thus, this paper suggests using thermal imaging in association with deep learning algorithms to detect microplastics at the water surface. Thermal imaging is a non-destructive testing method that allows for rapid and efficient screening of various materials and environments, including soil, water, and sediment. To date, the literature in this field is limited, with only one published study investigating the efficacy of active infrared imaging-based technologies for microplastic detection in sand particles. This pioneering research proposes active thermography as a potential pre-detection method to identify microplastic contamination [17].

In this paper, the prospect of thermal imaging to detect microplastics at the water surface is explored. Also, the combination of deep learning algorithms to accelerate the identification process is researched. The strengths and limitations of this proposed method are discussed.

3. Materials and methods

3.1. Data collection

3.1.1. Thermal camera

Contemplating active thermography as a promising non-destructive testing strategy for microplastic detection, PTi120 Pocket Thermal Imager is utilized to acquire the required dataset. PTi120 Pocket Thermal Imager is a versatile, reliable handheld device used to capture thermal images of samples in situ without the need for complex sample preparation or equipment. With an infrared resolution of 120 x 90 and a temperature range of -20 to 400°C, this thermal imager equips straightforward troubleshooting and quickly inspects the temperature of the target.

3.1.2. Experimental setup

Before data collection, the thermal imager is set up by adjusting the focus, emissivity, and other settings to ensure precise and consistent findings. The environment is considered to be devoid of hindrances that can tamper with temperature readings. Ambient temperature is managed by removing any objects that may reflect or emit heat, ensuring that there is no direct sunlight or other sources of heat, and minimizing air currents that may influence the temperature of the target. Fig. 1 depicts the experimental setup.

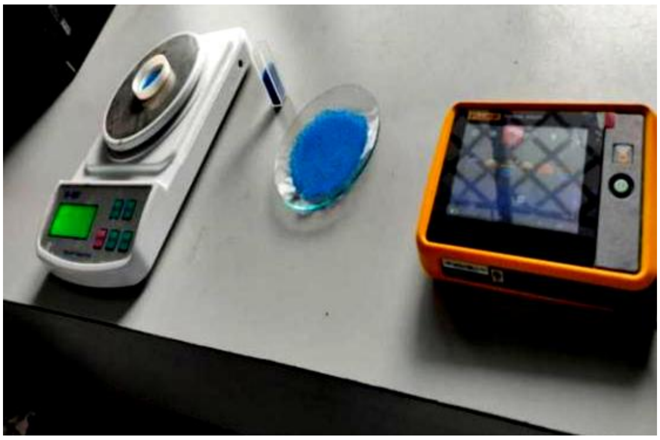

Fig. 1. Experimental setup (colour online)

3.1.3. Particles tested

In this experiment, the aim is to identify the lighter microplastics that float on the water surface and get carried away easily from the source. Thus, Low-density Polyethylene (LDPE), one of the most prominent plastic contaminants observed in water, was chosen as the detection sample. LDPE is extensively utilized in everyday products like disposable bottles, plastic bags, and food packaging, all of which can wind up in the water bodies when discarded inappropriately. The sample consists of microplastic particles of granular shape and sizes ranging from 2 to 3 mm.

3.1.4. Dataset

The dataset consists of images of diverse combinations of water, soil, and microplastics at different ratios, as this technique is sensitive to the concentrations of microplastics. In order to imitate the in-situ surface water backdrop, these combinations are taken into account. For comprehensive data collection, images are captured at multiple angles and distances from the samples at room temperature. The sample dataset is given in Fig. 2.

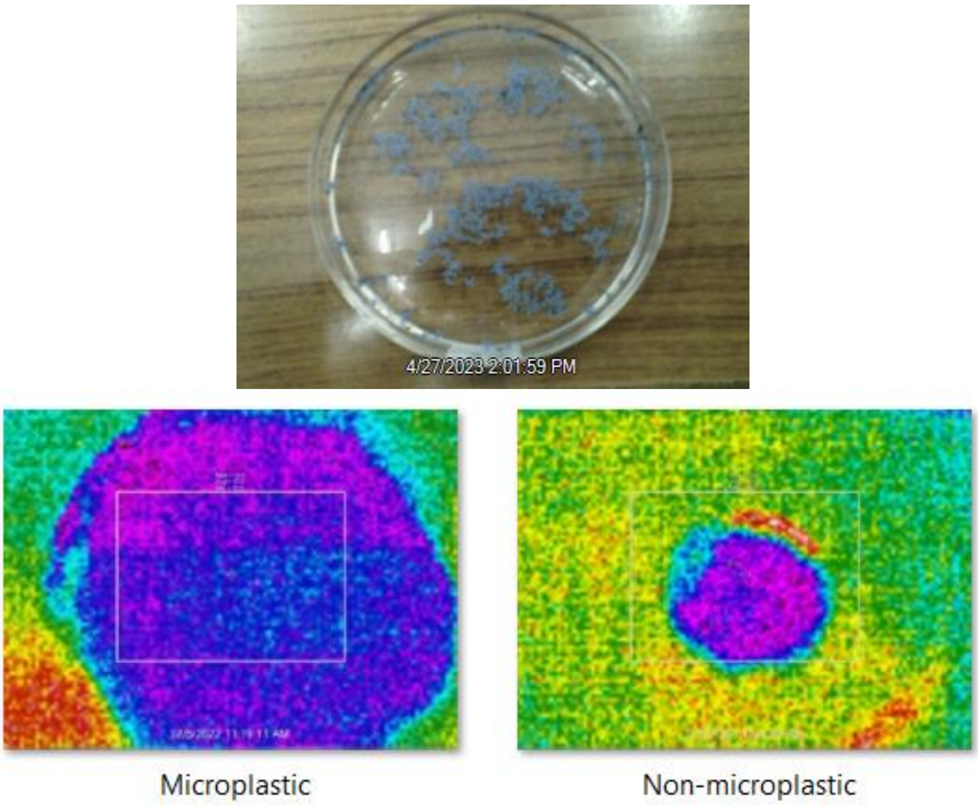

Fig. 2. Sample dataset (colour online)

3.2. Data pre-processing

Enhancement and normalization techniques may alter the pixel values and distribution in the image, causing distortion of certain features. Thus, a pre-processing pipeline is designed, taking into account the trade-offs of potential information loss and feature enhancement. Firstly, it is ensured that all images are in the same format and resolution to keep consistency. Then, the dataset was annotated with labels denoting the types of images, such as "microplastic" and "non-microplastic." This step makes it easier to train deep-learning models to identify microplastics.

Data augmentation was performed to expand the dataset size and lessen over-fitting when training a deep-learning model. By rotating each image at different angles clockwise, the final dataset was augmented five-fold to 2000 images equally split into the following categories: microplastic and non-microplastic. It is ensured that the dataset has a balanced representation of each class to avoid biases during training. Later, the dataset is divided by 7:2:1 to create a training, validation, and testing dataset. To assure the even-handedness of the test, the images in the testing dataset do not occur in training or validation.

3.3. Image classification

Machine learning composes a subset called "Deep learning" that strives to prepare neural networks to comprehend intricate data structures. Here, neural networks are crafted of numerous layers of interconnected nodes that understand to extract beneficial features from the input data through forward and backward propagation. Lately, deep learning has revolutionized the domain of image classification to open up a new scope of research. Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) are the two deep learning algorithms considered for this experimentation. By training these algorithms with our dataset, we aim to gain insights into the performance of each model in comparison to one another.

Deep Neural Networks (DNN) are general-purpose artificial neural networks. It incorporates numerous hidden layers between the input and output layers, trained using backpropagation to minimize the disparity between the actual and the predicted output. [2]. Convolutional Neural Networks (CNN) are specifically designed to capture spatial information in images. They use convolutional layers that detect local patterns and features in images, making them notably effective for image classification [18]. Thus, CNN is considered a good choice for this use case. DNN can be trained on a smaller dataset and still achieve reasonable accuracy, which is advantageous in this application as data collection is limited or expensive. Also, the DNN model is considered a good choice as it surpasses the CNN model in terms of simplicity and computation time.

3.3.1. Implementation of DNN model

The model architecture is defined as a sequential model, starting with a Flatten layer of input shape (128,128,3) tracked by a Dense layer with 12 neurons and activation function "ReLU"; a Dropout layer with 0.4 probability rate to prevent overfitting, and again, a Dense layer with 10 neurons and activation function "ReLU" and a Dense layer with two neurons and activation function "softmax" to output binary classification probabilities. The model is then compiled with Adam optimizer and binary cross-entropy loss with a 0.001 learning rate as they assist in consolidating an optimal solution with higher accuracy and efficiency.

3.3.2. Implementation of CNN model

The model architecture is devised by defining the sequence of each layer. The convolutional layer employs 32 filters and 64 filters with a 3×3 kernel as a filter and a ReLU activation function. Then, a max pooling layer probes for the utmost value within a 2×2 matrix and is tracked by Flatten layer and 2 Dense layers with 14 neurons and the activation function "ReLU". The model ends with a Dense layer with two neurons for two classes, namely microplastics, and non-microplastics. The model is then compiled with Adam optimizer and binary cross-entropy loss with a 0.001 learning rate as they assist in consolidating an optimal solution with higher accuracy and efficiency.

4. Results and discussion

The models were implemented in Python Language in the system with configuration as Intel(R) Core (TM) i5-10210U CPU, 64-bit OS, and 8 GB RAM. Keras, a Python library designed particularly for devising neural networks for machine learning models, is used with TensorFlow to train the neural network. The model is tested and evaluated based on the performance metrics like accuracy and precision. The models have been modified accordingly by improving the network design, randomizing the training dataset, and handling the overfitting and underfitting problems. In this two-class classification problem, the CNN model performs better than the DNN, with an accuracy of 97.42%. The comparison of accuracy and precision metrics for the DNN and CNN model is given in Table 1. Fig. 3 depicts the accuracy plot for both models.

Table 1. Comparative analysis of model performance

Model	Accuracy	Precision
DNN	85.05 %	87.15 %
CNN	97.42 %	87.19 %

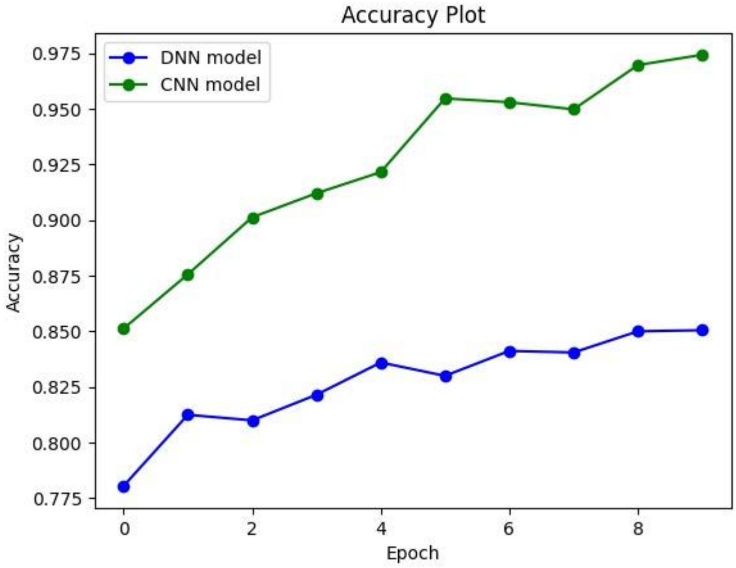

Fig. 3. Accuracy plot (colour online)

From the results, it is evident that thermal imaging has the potential to be a beneficial tool for detecting microplastics in surface water, considering its high sensitivity, non-destructive nature, high resolution, efficiency, and versatility. Thus, thermal imaging techniques in association with deep learning algorithms can produce quick and insightful results in microplastic detection, especially, the lighter microplastics that float at water's surface.

4.1. Discussions

However, thermal imaging has size limitations and is incompetent to detect microplastics that are smaller than the resolution limit of the thermal camera. The size range depends on the specificities of the camera. Thus, as the size of the microplastics diminishes, they may go barely noticed using thermal imaging alone. Thermal imaging is unsuitable for distinguishing microplastic types based on attributes like shape, color, etc. Also, different types of microplastics may have similar thermal properties, making it difficult to distinguish them solely based on thermal imaging.

Additionally, environmental factors such as ambient temperature, air movement, humidity, and the presence of other materials in the environment may produce false positives or interfere with the detection of microplastics. Thus, collaborating thermal imaging techniques with other complementary imaging techniques would improve the reliability of detection. Thermal imaging is predominantly reliable for surface-level detection only. It may not work well for finding microplastics embedded within sediments, soils, or other matrices, because the restricted penetration depth of thermal radiation bounds its utility in detecting microplastics in subsurface or opaque materials. Conducting exhaustive field studies to validate the efficacy of thermal imaging for microplastic detection is paramount. But, to develop an extensive dataset of exclusive images, it requires additional time and effort. Therefore, it is advisable to establish a collaborative dataset for future work. Continuous advancements in integrating thermal imaging technology with one or more complementary imaging techniques, such as spectroscopy, microscopy, or chemical analysis, can provide a more comprehensive analysis of microplastics.

Also, incorporating the proposed work with automated systems can help to gather real-time data over extended periods, allowing for a sounder comprehension of microplastic distribution and trends. As deep-learning models are still advancing, increasingly diversified models can be employed using the proposed approach. In essence, computer vision methods play a vital role in this ever-growing field by expediting the identification and classification of microplastics.

5. Conclusion

The objective is to offer researchers a tool to expedite the identification of microplastics at the surface level with better accuracy. Aiming to identify the lighter microplastics that float on the water surface and get carried away easily from the source, the microplastic sample chosen is Low-density Polyethylene (LDPE). We have collected the dataset using the thermal imaging technique, taking into account the diverse combinations of water, soil, and microplastics. The study adopted a deep learning-based approach for image classification, and the reported best accuracy, 97.42%, is achieved using the CNN model. The proposed approach can help streamline the identification process of microplastics, benefiting both researchers and the environment. Also, considering the use case and possibilities, the project has a great future scope of work.

Data availability

The data that support the findings of this study are available from the corresponding author E Manikandan, upon reasonable request.

Credit authorship contribution statement

E Manikandan: Conceptualization, Data collection, **Sheena Christabel Pravin** Writing - Review & Editin**.** **Kiruthika V** – Methodology, Supervision, Editing, **S Gopikashree:** Data collection, Methodology, Software, Writing - Review & Editing, Writing - Original Draft. **Sai Gokul Chandan H.T:** Data Collection, Methodology, Review, **K A Karthigeyan** – Data collection & Methodology, **S.Shoba** – Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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