MICROPLASTIC DETECTION IN WATER USING IMAGE PROCESSING

A

PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

IN

CIVIL ENGINEERING

Under the supervision

of

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HIMACHAL PRADESH INDIA

MAY, 2022

DECLARATION

I hereby declare that the work presented in the Project report entitled **"MICROPLASTIC DETECTION IN WATER USING IMAGE PROCESSING"** submitted for partial fulfillment of the requirements for the degree of Bachelor of Technology in Civil Engineering at **Jaypee University of Information Technology, Waknaghat** is an authentic record of my work carried out under the supervision of **Dr. Rishi Rana.** This work has not been submitted elsewhere for the reward of any other degree/diploma. I am fully responsible for the contents of my project report.

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CERTIFICATE

This is to certify that the work which is being presented in the project report titled **"MICROPLASTIC DETECTION IN WATER USING IMAGE PROCESSING"** in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Civil Engineering submitted to the Department of Civil Engineering, **Jaypee University of Information Technology, Waknaghat** is an authentic record of work carried out by **Abhinesh Thakur (181639) and Dechen Tshomo (181654)** during a period from August 2021 to May 2022 under the supervision of **Dr. Rishi Rana** (Assistant Professor, Senior Grade), Department of Civil Engineering, Jaypee University of Information Technology, Waknaghat.

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ABSTRACT

Microplastics have lately been identified as significant pollutants in all environmental matrices. Microplastic pollution is a growing environmental concern. The majority of studies have focused on microplastic pollution in marine waters; however, little is known regarding the prevalence of microplastics in freshwater systems. Seasonality should be taken into account when analyzing microplastic abundance in water bodies since it has an impact on microplastic presence in aquatic systems. Their quantification and characterization necessitate lengthy and time-consuming analytical techniques, making this an important part of microplastics study.

In this research we are using a Computer Vision and Machine-Learning-based system to count and identify microplastics quickly and automatically, eliminating the need for manual procedures. Microplastics will be counted and classified using an early machine learning technique. The machine learning technique is expected to produce promising results in terms of counting and size classification. Finally, the suggested application will provide a dependable automated method for microplastic quantification based on counts of particles

In this work OpenCV-Python is used to process 8 different images of microplastic samples acquired from previous studies and publications in this project because collecting samples on our own is challenging due to the current pandemic condition.

Key words: *Microplastics, Computer Vision, Freshwater, Quantification, Automatic.*

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LIST OF ACRONYMS & ABBREVIATIONS

MP	Microplastic
OpenCV	Open source Computer Vision
ML	Machine Learning
WWTP	WasteWater Treatment Plant
NOAA	National Oceanic and Atmospheric Administration
UV	Ultraviolet
PS	Polystyrene
EPS	Expanded Polystyrene
HDPE	Low-density Polyethylene
LDPE	High-density Polyethylene
PA	Polyamide
PP	Polypropylene

ABS	Acrylonitrile-butadiene-styrene
PTFE	Polytetrafluoroethylene
CA	Cellulose Acetate
PC	Polycarbonate
PMMA	Polymethyl methacrylate
PVC	Polyvinyl chloride
PET	Polyethylene terephthalate

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Richard Thompson, a marine biologist at the University of Plymouth in the United Kingdom and Professor introduced the term “microplastics” in the year 2004 [1].

According to the U.S. National Oceanic and Atmospheric Administration (NOAA) and the European Chemicals Agency, microplastics are fragments of any type of plastic less than 5 mm (0.20 in) in length [1,3]. MPs cause contamination in normal ecosystems by entering from different assortment of sources, including beauty care products, clothing, and industrial cycles.

Microplastics are normal in our present reality. In 2014, it was assessed that there are somewhere in the range of 15 and 51 trillion individual bits of MPs on the planet’s seas, which was assessed to weigh somewhere in the range of 93,000 and 236,000 metric tons [6,8].

Since plastics corrupt gradually (frequently more than hundreds to millennia), MP particles stand a greater likelihood of ingestion, consolidation into, and collection in the body as well as tissues of numerous life forms[5,8]. In earthbound environments, MP particles have been exhibited to decrease the practicality of soil biological systems and lessen weight of worms. The cycle and development of MP particles in the climate are not completely known, yet research is in progress to explore wonders.

1.2 CHEMICAL NATURE OF MICROPLASTICS

Plastic is mostly made from fossil fuels, but biomass is occasionally utilized as a feedstock. Polyethylene (PE), Polypropylene (PP), polyethylene terephthalate (PET), polyvinyl chloride (PVC), and polystyrene (PS) are the most common plastic polymers, accounting for over 90% of global plastic manufacturing. These polymers are nonbiodegradable and have a high molecular weight. As a result, they are constantly present in the environment. PE, PP, PVC, PS, PET, and PUR resins account for 29, 19, 12, 8, 6, and 7% of total global output, respectively. Carbon and hydrogen are fundamental components in nearly all plastics, and

PVC also contains chloride as a major component alongside carbon and hydrogen. To i0mprove the performance of plastics, a number of additives such as thermal stabilizers, inorganic fillers, plasticizers, UV stabilizers, and fire retardants are used [22,20].

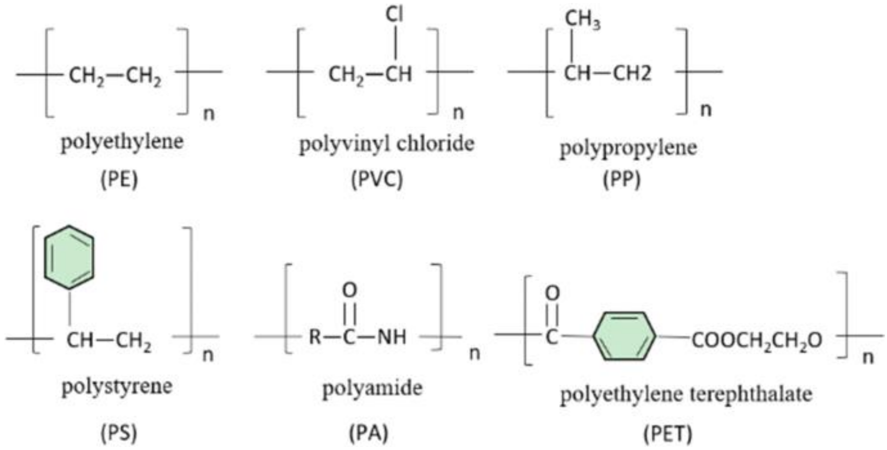


Figure 1.1 Chemical structures of microplastics (Source: [13])

1.3 DEGRADATION OF PLASTICS

Degradation is the chemical alteration of a polymer's structure to reduce its molecular weight. The most essential characteristic of synthetic polymers is their high resilience to environmental conditions, which extends their residence duration and reduces environmental deterioration. During the degradation process, polymers are broken down into smaller molecular units called oligomers and monomers. There are two types of degradation of synthetic polymers: biotic and abiotic [19,44].

UV-B radiation from the sun is the principal source of photo oxidative degradation in low-density polyethylene (LDPE), high-density polyethylene (HDPE), PP, and nylons. Thermo-oxidation can help to speed up the deterioration process [19]. Polymers become embrittled as a result of extensive breakdown, resulting in micro and nano-sized plastics. Microorganisms degrade these micro and nano pieces further. The time required for complete mineralization of plastic is estimated to be between a hundred and a thousand years. Because of the decreased exposure to UV light and oxygen in aquatic systems, plastic breakdown is slower than in terrestrial systems [44].

1.4 CLASSIFICATION OF MICROPLASTICS

1.4.1 Primary microplastics

Primary MPs are small bits of plastic which have been deliberately fabricated. They are normally utilized in facial cleaning agents and beauty care products, or in air impacting innovation. These processes include impacting acrylic, melamine, or polyester microplastic scrubbers at apparatus, motors, and boat structures to eliminate paint and rust. As these scrubbers are utilized over and over until they decrease in size and their cutting force is lost, they frequently become polluted with heavy metals like cadmium(Cd), chromium(Cr), and lead(Pb). There are numerous bioplastic microbeads that have a long degradation life cycle like ordinary plastic, although many organizations are focused on lessening the creation of microbeads [1,2].

1.4.2 Secondary microplastics

Secondary microplastics are little bits of plastic got by the breaking down of bigger debris of plastic, both on land and at sea. This process whereby huge plastic matters disintegrate into smaller bits is known as fragmentation [5,7,19]. MPs may further breakdown into smaller size, though the smallest MP particle apparently recognized in the seas at present is 1.6 micrometers (6.3×10^{-5} in) in diameter. The predominance of MPs with irregular shapes is a prove that fragmentation is the main source of MPs.

Table 1.1 Shape classifications of microplastic particles (Source: [12])

Microplastic shape classification	Description
Fragments	Irregular shaped particles, granules, crystals, flakes, films
Fibers	Filaments, microfibers, thread like, strands
Pellets	Beads, nurdles

1.5 SOURCES OF MICROPLASTIC

Most MP contamination comes from the clothing, tires and urban pollution which are responsible for more than 80% of all MP pathogens in the climate.

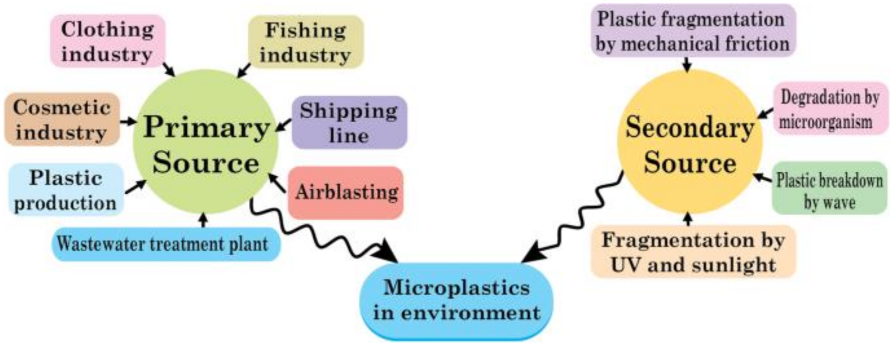


Figure 1.2 Sources of microplastic (Source: [4])

1.5.1 Manufacturing

Manufacturing of plastic items utilizes granules and little pellets as their crude material. Through incidental spillage during land or water transportation, improper use as packaging materials, these crude materials can enter aquatic ecosystem. There is a huge lack of research focused on companies and organizations that contribute to microplastics contamination.

1.5.2 Cosmetics industry

“Micro-exfoliates” or “microbeads” are made out of polyethylene, a typical part of plastic. Face washes, hand cleansers, and other personal and beauty care items contain these beads. Their small size keeps them from completely being retained by screens of preliminary treatment at wastewater plants. Wastewater treatment just eliminates a normal of 95–99.9% of micro beads due to their small design. Taking into account that one treatment plant releases 160 trillion liters of water each day, 8 trillion microbards are delivered into waterways each day. Even when the item is eliminated from cosmetic items, unsafe items are still being sold with have plastics in them.

1.5.3 Clothing

Studies have shown that numerous synthetic fibers, like nylon, acrylics, polyester, and spandex, can be shed from clothing and persist in the environment. Each item in a heap of clothing can shed in excess of 1,900 strands of microplastics. For a normal wash heap of 6 kilograms (13 lb), more than 700,000 fibers could be released per wash. Primary fiber that endures all through the clothing business is polyester which is a cheaper cotton alternative that can be easily produced. The methods involved with washing garments makes articles of clothing lose a normal of more than 100 fibers for each liter of water.

1.5.4 Sewage treatment plants

With a removal efficiency of about 99.9%, one molecule for every liter of microplastics is being delivered back to the environment,. Sewage treatment plants eliminate pollutants from wastewater, essentially from household sewage. Microplastics pass through the filtration processes at some WWTPs. In some countries, sewage sludge is used for soil fertilizers, exposing the plastic present in sludge to sunlight, weather and other biological variables, causing fragmentation. From these biosolids the microplastic frequently ends up in storm drains and eventually into the water bodies.

1.5.5 Fishing industry

Commercial and recreational fishing, maritime boats, and the marine industry are all sources of plastic that can enter the marine environment directly. Beaching of items carried by inshore and ocean currents also results in the accumulation of marine debris on beaches. Fishing gear is a type of marine-derived plastic waste. Lost or discarded fishing gear, such as plastic nylon netting and monofilament line, is usually neutrally buoyant and can float at different depths in the ocean. MPs from industry and other sources have been found in many types of sea foods, according to reports from various countries.

1.5.6 Shipping and packaging

The shipping industry has made a considerable contribution to maritime pollution. According to some estimates, commercial cargo fleets throughout the world spilled over 23,000 tons of plastic garbage into the ocean in 1970. The dumping of rubbish from ships into the marine environment was forbidden by an international agreement (MARPOL 73/78, Annex V) in 1988. Shipping continues to be a major source of plastic pollution, accounting for roughly 6.5 million tons in the early 1990s.

1.6 POTENTIAL CONSEQUENCES OF MICROPLASTICS

Microplastics are now found in every element of the ecosystem, according to a comprehensive analysis of scientific evidence published by the European Union's Scientific Advice Mechanism in 2019.

Microplastics have been found in freshwater systems such as streams, marshes, ponds, rivers, and lakes, as well as in marine systems (South America, Asia and Australia, Europe, North America).

1.6.1 Microplastic ingestion into aquatic organisms

MPs can become entrenched in the tissue of animals, through respiration or ingestion. Microplastics can take up to 14 days to pass through an animal, but entanglement of the particles in the gills of animals can hinder removal completely. Plastic particles are frequently mistaken as food by fishes there by clogging their digestive processes and transmitting false feeding signals to their brains. Chemical contaminants can also be absorbed by microplastics and transmitted into the tissues of the organism. The presence of microplastics in the intestines of 11 species of coastal freshwater fish was discovered in the Argentinean shore of the Rio de la Plata estuary.

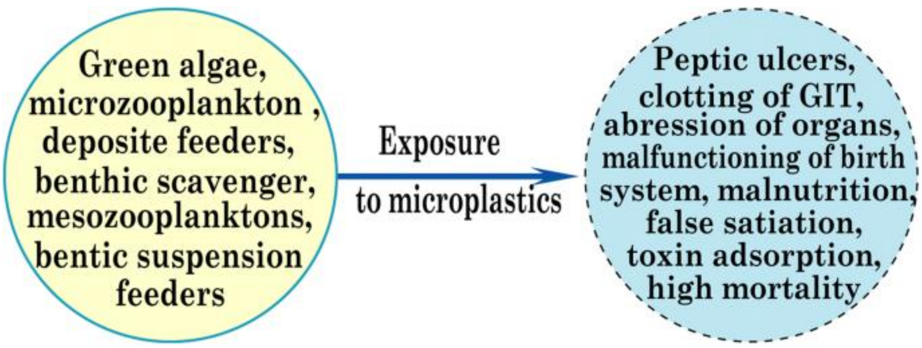


Figure 1.3 Effect of microplastics on aquatic organisms (Source: [4])

1.6.2 Effect of microplastic on human health

The entry of hazardous chemicals and microplastics into the food web can endanger human health. Microplastics are consumed by a number of marine species, which are then eaten directly by humans, according to various studies. Microplastics have also been studied in the gastrointestinal tracts of individuals who eat freshwater fish. Nonetheless, the level of microplastic absorption by intestinal cells and their translocation into the tissues of aquatic creatures determines the risk of microplastics to human health.

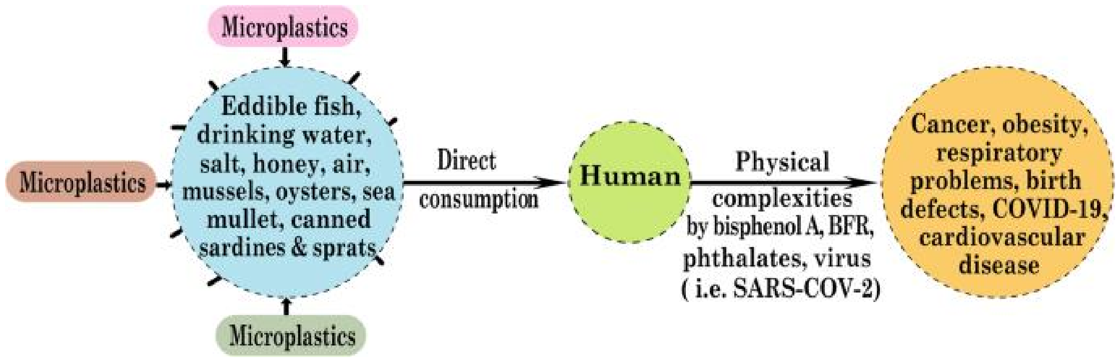


Figure 1.4 Effect of microplastics on Human health (Source: [4])

1.6.3 Occurrence of microplastics in freshwater system

Microplastic has been found in several compartments of freshwater habitats, including sediments, according to recent investigations (Wagner and Lambert, 2018). Micro and macro plastics were initially discovered in lakes in Switzerland (Faure et al., 2012) and in a subalpine lake in Italy (Faure et al., 2012). As a result, several researches on the deterioration of water bodies, such as lakes, estuaries, and rivers, as well as macro and micro plastic contamination, have been undertaken and published. Nonetheless, in different research, measurement of microplastic has been done using different methodologies, which makes comparability of results problematic.

1.6.4 Buoyancy

Around half of the plastic material delivered to the marine environment is buoyant. Foul fouling by organisms can cause plastic trash to sink to the sea floor, interfering with sediment-dwelling species and sediment-gas exchange processes. This problem is especially serious in the case of larger plastic trash. On the ocean's surface, MPs can also form a bio-film layer that is buoyant in nature. The microplastics' buoyancy is a direct result of density of the plastic it is made of, the shape and size of the microplastic fragments themselves.

Table 1.2 Density of different types of plastic (Source: Microplastics - Wikipedia)

Plastic Type	**Abbreviation**	**Density(g/cm^3)**
Polystyrene	PS	1.04-1.08
Expanded Polystyrene	EPS	0.01-0.04
Low-density Polyethylene	HDPE	0.94-0.98
High-density Polyethylene	LDPE	0.94-0.98
Polyamide	PA	1.13-1.16
Polypropylene	PP	0.85-0.92
Acrylonitrile-butadiene-styrene	ABS	1.04-1.06
Polytetrafluoroethylene	PTFE	2.10-2.30
Cellulose Acetate	CA	1.30
Polycarbonate	PC	1.20-1.22
Polymethyl methacrylate	PMMA	1.16-1.20
Polyvinyl chloride	PVC	1.38-1.41
Polyethylene terephthalate	PET	1.38-1.41

1.7 SEASONAL VARIATIONS OF MIROPLASTICS

Seasonality can have an impact on the rate of microplastic buildup in sediments. Microplastic abundance in aquatic systems has been linked by freshwater researchers to rain events. During rainy seasons, surface runoff promotes microplastic entry into storm drains, rivers, streams, and eventually the marine environment [7,9].

Microplastics can be trapped by frozen soil in the winter and released during spring flooding; therefore seasonal trends can have an impact on their accessibility in catchment areas. Thawed soil is better at releasing microplastics into the environment. During growth seasons, this might result in a larger influx of microplastics, which is amplified by additional particles released by snow melting [9,11,17].

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

This chapter includes critical analysis of various articles, books and journals about detection of microplastics. Different literature has been evaluated, which helped us in understanding different methods and techniques used for the detection of microplastics. In this chapter we could also identify the research gaps. Brief summary of few other research papers are also provided below.

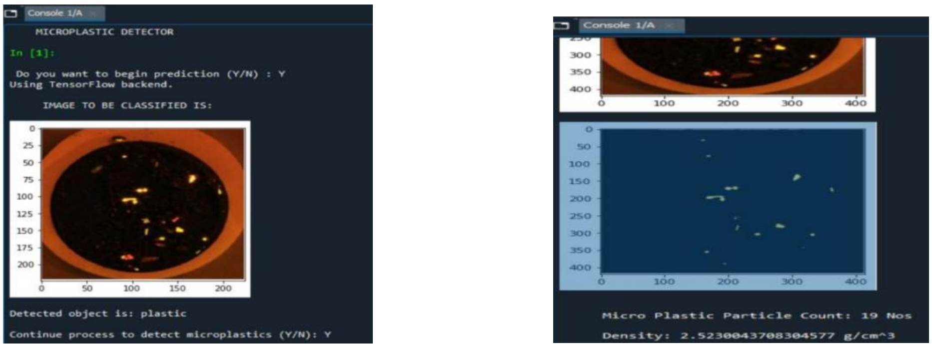
2.1.1 Shivika Sharma and Subhankar Chatterjee, April 2017, Microplastic pollution, a threat to marine ecosystem and human health, Environ Sci Pollut Res (2017)

They conducted a general investigation into plastic pollution in the marine ecology in their report. They conclude that plastic pollution in the marine ecosystem is a serious problem since it is ubiquitous in the natural environment, has detrimental impacts on marine biota, and is passed down the food chain. They also emphasize the necessity of raising public knowledge about microplastic pollution and implementing various public awareness initiatives and campaigns. They also offer some future approaches in this paper, such as the government establishing a "zero tolerance" policy for this issue and requiring enterprises to utilize biodegradable materials such as starch rather than non-degradable materials.

2.1.2 Neeta K, et al., 2020, Microplastic detection in water using image processing, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 15

The study proposes assessments of the currently used methodologies for detecting the presence of microplastics in water, with an emphasis on the most practical techniques and approaches. For image classification, they employ the deep learning CNN method.

In this study they use image processing to detect the presence of microplastics in water. The detection of microplastic takes place in two stages: training stage and testing stage. For classification, a deep learning architecture called the Convolution Neural Network (CNN) is used. CNN method was used to analyze and classify photos of water taken in real time.



(a) **(b)**

Figure 2.1 (a) Detection of microplastics; (b) microplastic count and density (Source; [1])

2.1.3 Shahina Karim, 21 June 2021,Seasonal variation of microplastic accumulation in lake sediments, University of Eastern Finland, Faculty of Science and Forestry

The aim of this research was to Figureure out seasonal variation of microplastic accumulation in lake sediments. The sediment trap technique was used to gather sediments from Lake Kallavesi, and the sediment trap monitoring lasted two years (winter 2016 – summer 2018). Microplastics were extracted from sediments using the heavy-liquid density separation method then the microplastics were visually selected under a stereo microscope for FTIR analysis. The FTIR spectra were examined using the siMPLe program. Winter samples had higher microplastic contents than summer samples.

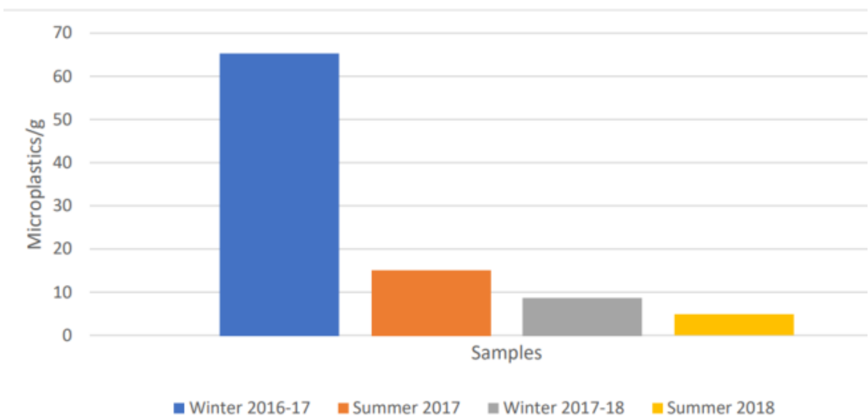


Figure 2.2 Concentration of microplastics in sediment samples (Source: [2])

2.1.4 Carmine Massarelli, et al., July 2021, A handy open-source application based on computer vision and machine learning algorithms to count and classify microplastics, Water Research Institute, Italian National Research Council (IRSA-CNR), 70132 Bari, Italy

In this research, they developed a Computer Vision and Machine Learning-based system to count and identify microplastics in four morphological and size categories rapidly and automatically, avoiding human procedures. The proposed application provided a viable automated method for microplastic quantification based on counts of particles caught in a photograph, size distribution, and morphology, with significant method standardization potential [3].

(a)

(b)

Figure 2.3 (a) MP sample before image processing; (b) MP sample after image processing

(Source: [3])

2.1.5 Javier Lorenzo-navarro, et al., January 2020, SMACC: A System for Microplastics Automatic Counting and Classification

In this report, they counted and classify microplastic particles (1-5 mm) into five visual classes automatically using a computer vision-based system. The technique starts with a segmentation stage that uses the Sauvola thresholding method, then moves on to feature extraction and classification. The technique was tested on a total of 2507 microplastic particles from 12 distinct beach samples.

2.1.6 Thuhin K. Dey, et al., July 2021, Detection and removal of microplastics in wastewater: evolution and impact, Environmental Science and Pollution Research (2021)

This study examines existing and newly developed methods for detecting and separating microplastics from discharged wastewater, which is one of the most difficult problems in microplastic treatment systems. They also discuss a critical study on the impact of microplastics on aquatic life and human health [6]. As a result, this study gives a thorough grasp of various strategies for detecting and removing microplastics, as well as their related difficulties, in order to provide a waste discharge standard that minimizes the final potential impact in aquatic habitats.

2.1.7 Viktor Wegmayr, et al., 2020, Instance Segmentation for the Quantification of Microplastic Fiber Images, Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)

In this report they employ a fiber instance detection pipeline, which breaks down fiber detection and segmentation into digestible chunks. Robust image processing techniques, such as adaptive threshold and morphological skeleton analysis, are used to identify well separated instances, while an algorithm based on deep pixel embedding is used to separate tangled fibers. Their method enhances out-of-sample data dramatically, especially in tough circumstances with intersecting fibers.

2.2 RESEARCH GAP

Most of the research papers and report done on microplastic detection and quantification involve laboratory techniques and manual procedures.

Manual quantification of MP particles is less reliable than automatic quantification.

2.3 RESEARCH OBJECTIVE

Demonstrating the presence of microplastic particles in real time and in fresh water sources.

Image processing of microplastic sample images and determining the exact number of particles contained in the images.

Automatic quantification and classification of MP using Machine-Learning based system (OpenCV Python) for accurate results and minimum error.

CHAPTER 3

METHODOLOGY

3.1 GENERAL

MPs in water samples were detected and automatically quantified using OpenCV-Python. Image processing using OpenCV-Python takes substantially less time than manual techniques and produces more accurate results. As sampling was difficult due to the current pandemic situation, real-time sample images from various sources were used for image processing.

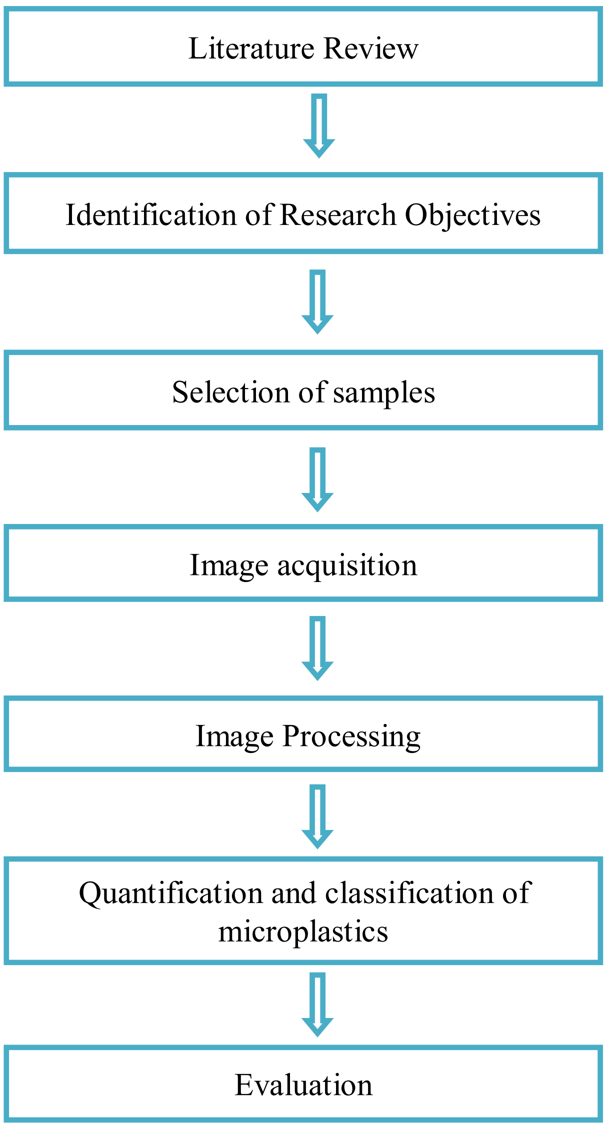


Figure 3.1 Research framework

3.2 IMAGE PROCESSING

Images define the world; each image contains a large amount of vital information that can be applied in a variety of ways. Image Processing is a technique that can be used to obtain this information.

It is the foundation of computer vision and is essential in many real-world applications such as robotics, self-driving cars, and object detection. Image processing allows us to transform and manipulate thousands of images at once while obtaining important insights. It has nearly limitless applications in almost every field.

Image quantification is the process of measuring image attributes using human sense or machine observations and experiences and mapping them into members of a set of numbers or coded concepts.

The two main tasks of digital image processing are:

i. Improving pictorial information for human interpretation
ii. Image data processing for storage, transmission, and representation for autonomous machine perception

3.2.1 OpenCV

OpenCV (Open Source Computer Vision) is an open-source library that contains hundreds of computer vision algorithms. OpenCV is accessible on a range of platforms, including Windows, Linux, OS X, Android, and iOS, and supports a variety of programming languages such as C++, Python, Java, etc.

The OpenCV package has a modular structure, which means it includes a number of shared or static libraries.

Modules in OpenCV are as follows:

i. Core functionality (core)
ii. Image Processing (imgproc)
iii. Video Analysis (video)
iv. Camera Calibration and 3D Reconstruction (calib3d)

v. 2D Features Framework (features2d)

vi. Object Detection (objdetect)

vii. High-level GUI (highgui)

viii. Video I/O (videoio)

The OpenCV-Python library is a set of Python bindings for solving computer vision issues. The fundamental advantage of OpenCV is its enormous access to algorithms, as well as its widespread use and algorithmic efficiency. OpenCV provides access to over 2,500 algorithms for deploying machine learning and computer vision capabilities such as object recognition and facial recognition.In this research the OpenCV version that we are using is 4.1.2.

```
[16] !pip install opencv-contrib-python

Requirement already satisfied: opencv-contrib-python in /usr/local/lib/python3.6/dist-packages (4.1.2.30)
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from opencv-contrib-python) (

%%cu
#include <opencv2/quality.hpp>
#include  <opencv2/opencv.hpp>
#include <opencv2/ml.hpp>
#include <opencv2/core.hpp>
using namespace cv::ml;
 using namespace std;
 using namespace cv;

    cv::Mat img = cv::imread("/content/src/566.png"); // path to the image to evaluate
    cv::String model_path = "/content/BRISQUE/brisque_model_live.yml"; // path to the trained model
    cv::String range_path = "/content/BRISQUE/brisque_range_live.yml"; // path to range file
    /* compute BRISQUE quality score via static method */
    cv::Scalar result_static = quality::QualityBRISQUE::compute(img,
model_path, range_path);
    /* alternatively, compute BRISQUE via instance */
    cv::Ptr<quality::QualityBase> ptr = quality::QualityBRISQUE::create(model_path, range_path);
    cv::Scalar result = ptr->compute(img); /* computes BRISQUE score for img */

/tmp/tmp2j1wb4o7/8217cf9b-e953-48e0-8a1b-c8ca9d50c00d.cu:1:10: fatal error: opencv2/quality.hpp: No such file or dire
 #include <opencv2/quality.hpp>
          ^~~~~~~~~~~~~~~~~~~~~
compilation terminated.
```

Figure 3.2 OpenCV [Source: 19]

3.2.2Python

Python is a widely used programming language for image processing. It's incredible libraries and tools aid in the efficient completion of image processing tasks.

Displays; basic manipulations such as cropping, flipping, rotating, and so on; picture segmentation, classification, and feature extractions; image restoration; and image recognition are all common image processing tasks. Due to its growing popularity as a scientific programming language and the free availability of numerous state-of-the-art image processing tools in its ecosystem, Python is a great choice for these types of image processing applications. In our research we are using Python version 3.7.13.

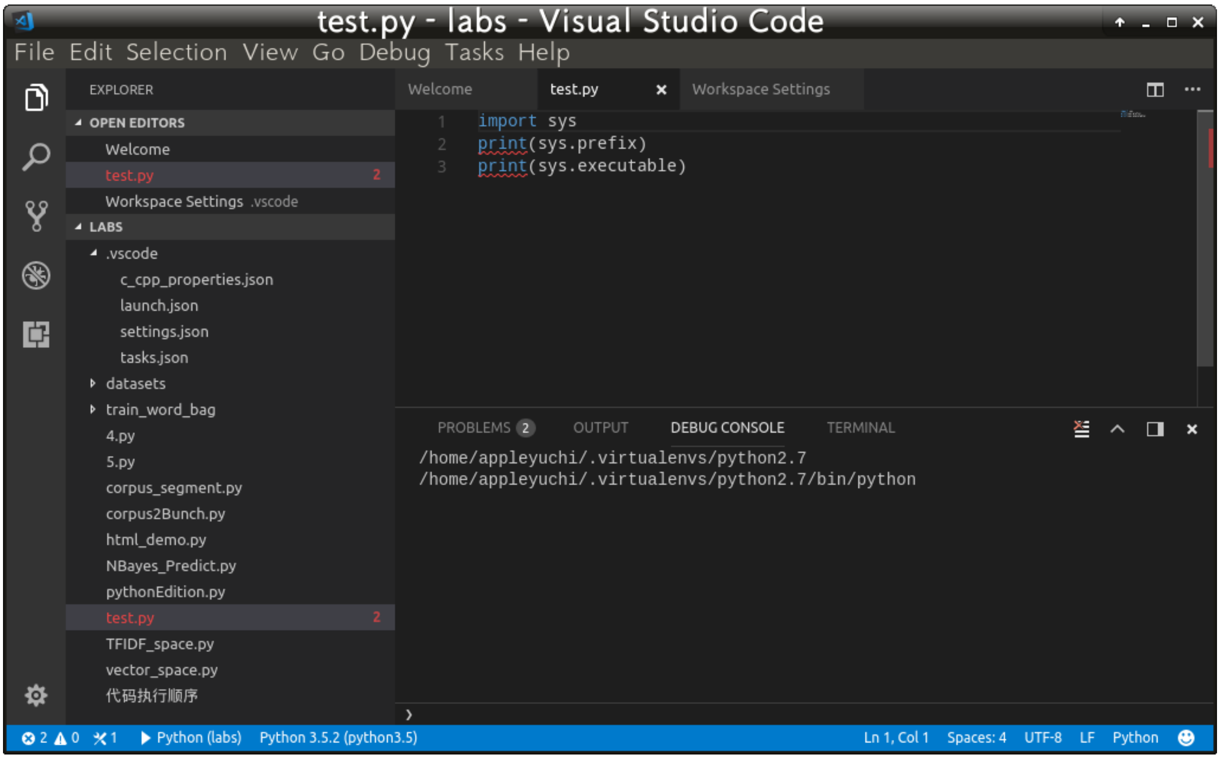


Figure 3.3 Python [Source: 20]

3.3 MATERIALS AND METHODS

3.3.1 Overall image processing workflow

To extrapolate information from a collected image, algorithms from open-source computer vision are employed. In addition, we employed a machine learning technique (based principally up on if-then-else expressions) to count and classify the microplastics based on their distinct features, such as ratio of size and morphologies, based on the outputs generated from the processing of the OpenCV software library.

Already clicked images of microplastic particles from water sources found from different online sources are processed in this report. Python is used for image processing. The library to be used is OpenCV a open source computer vision library which has almost all the functions required to perform the image processing work on the sample images of the microplastic particles. The images will be processed and then the count of particles present in each sample image will be generated. Following flow chart shows how the image processing will work.

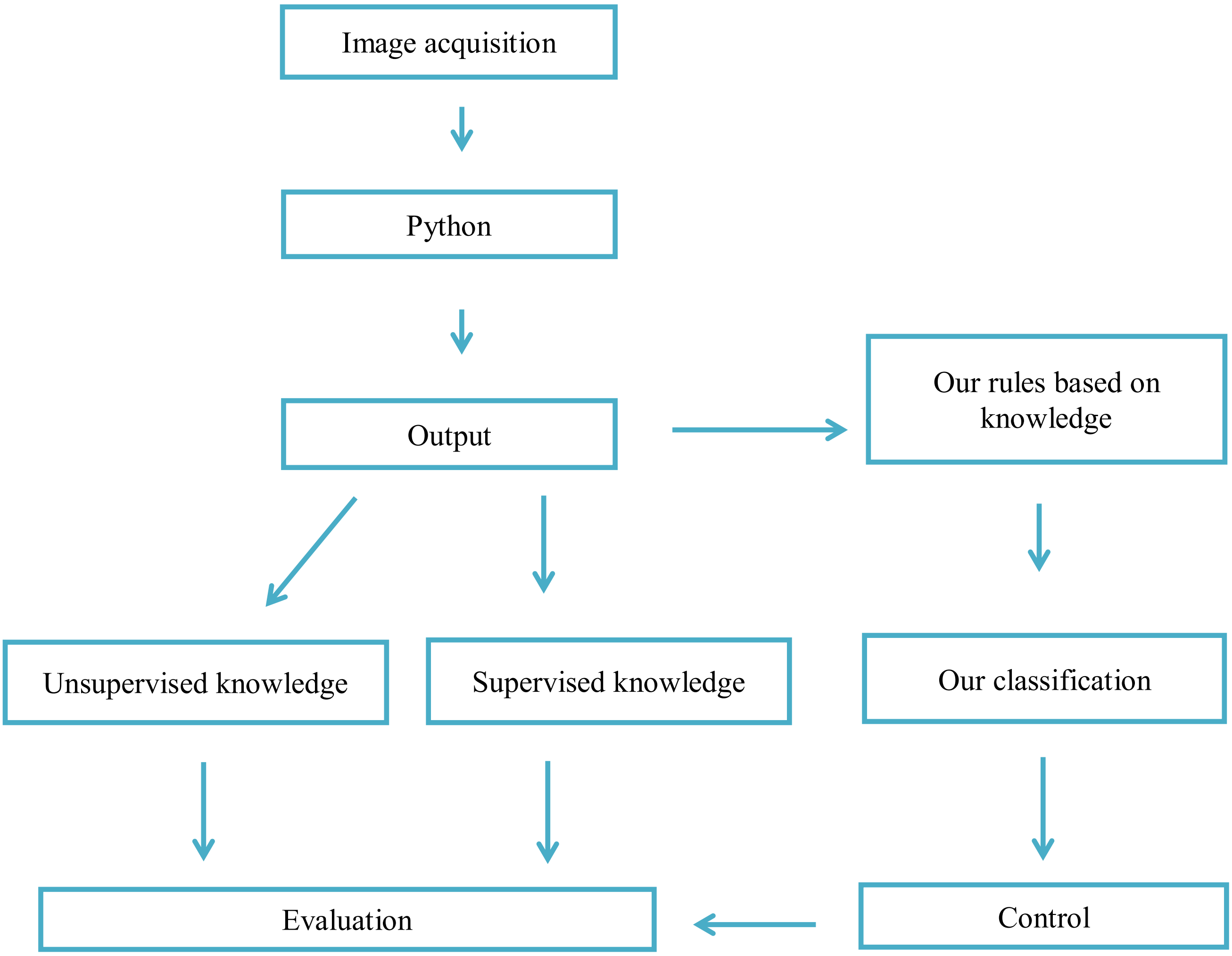
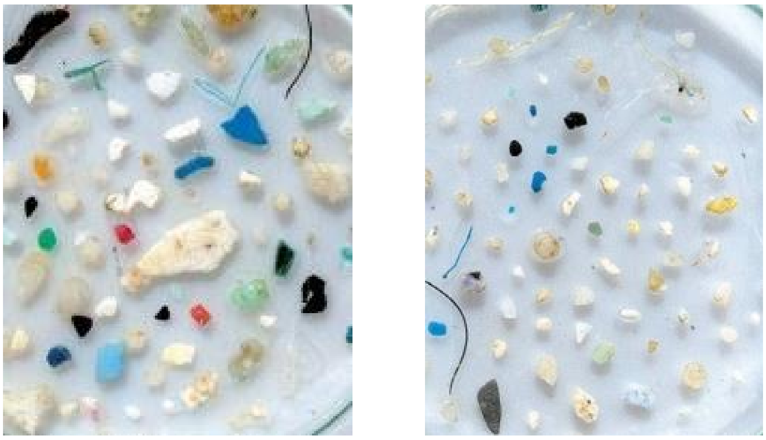


Figure 3.4 Image processing workflow

3.3.2 Sample image acquisition

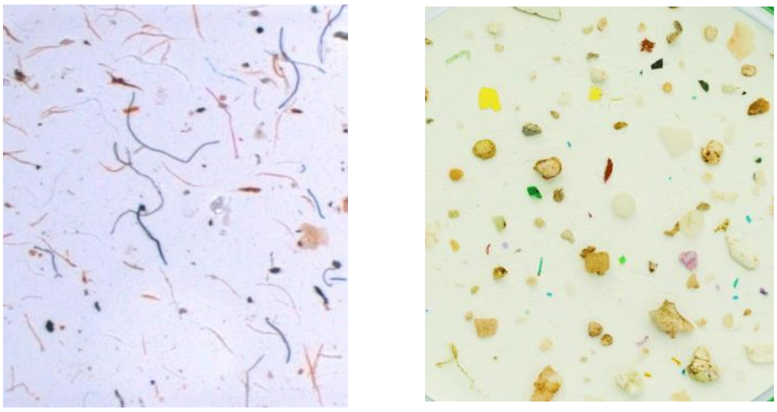
Acquisition of image can be done with any digital camera, it can be the simple cameras found on smart phone to the more complex cameras found in digital microscopes. It is preferable to utilize cameras with high-resolutions placed over a tripod and operated with a remote control to obtain an image totally orthogonal to the focal plane and, much better, to eliminate any vibration that could cause a little shadow exchanged by a particle contour. Even using a smart phone camera has shown to be beneficial because, to date, these devices have powerful software tool for regulating the acquisition process, including the ability to reduce motion blur while same resolution being maintained and boosting image quality (contrast, sharp colors, etc) automatically.



(a) **(b)**

Figure 3.5 (a) sample 1; (b) sample 2

(Image source: Samuel Bollendorff – Tara Expeditions Foundation)



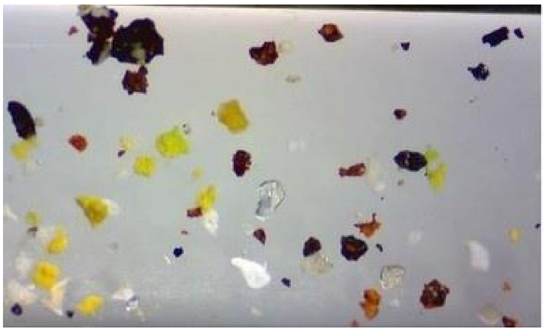
(a) **(b)**

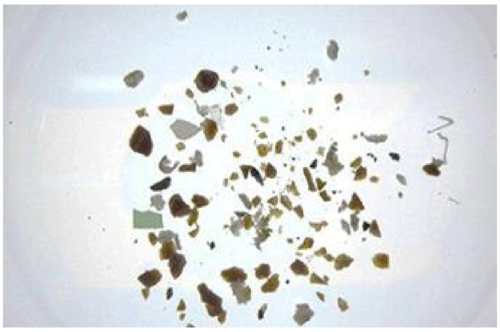
Figure 3.6 (a) sample 3; (b) sample 4

(Image source: sample 3 from Research Gate and sample 4 by Kevin Tallec)

In hand-made images, however, the presence of a minor distortion has no bearing on the categorization performed by the algorithm, which takes into account numerous variables rather than just one, as well as distinct rules and their ratios, as illustrated in the next section. The smaller the minimum size of detectable microplastics, the higher the camera's resolution power. The resolution will be higher or lower depending on the image quality [4,33.21]. High-resolution photos indicate a higher level of particle detail, but also a more obvious identification of any background flaws. This could introduce noise that could be confused with certain forms of microplastics, leading to the measurement ofparticles other than MP particles [22,30].

For our research we acquired sample photographs of MP captured in real time from other sources to proceed with the image processing because capturing samples on our own was challenging. To move on, a total of eight freshwater sample photos are considered as shown below [47].

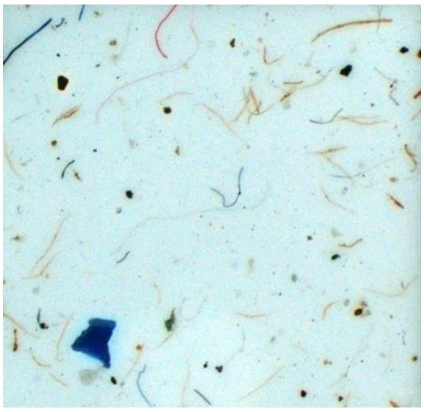


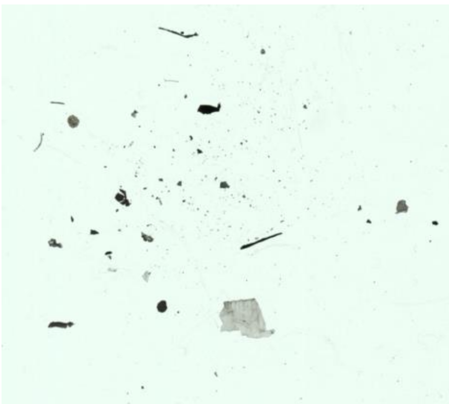


(a) **(b)**

Figure 3.7 (a) Sample 5; (b) Sample 6

(Image source: Sample 3 from Ecologica Montenegrina and Sample 6 from MitsuiO.S.K. Lines)





(a) **(b)**

Figure 3.8 (a) Sample 7; (b) Sample 8

(Image source: Sample 7 from Jean-Pierre Desforges, Vancouver Aquarium and Sample 8 from Research Gate)

3.3.3 Machine Learning workflow

Computer vision research aims to transfer human perceptions to computers, allowing them to detect the surroundings, take actions, and learn from the experiences. Target recognition, manufacturing, photo interpretation, remote sensing, and navigation are all examples of real-world challenges that computer vision systems are employed to tackle [18,19]. Machine learning, on the other hand, is the concept that computer algorithms and information and communication technology (ICT) systems can improve their performance over time, progressing from general-purpose learning systems to symbolic learning of high-level knowledge and artificial neural networks[44]. Because of the learning-based approach, machine learning algorithms have been popular in recent years as a very reliable tool for developing computer vision performance. In this research we intend to find solutions to practical problems.

We are using an application based on OpenCV Python Application Programming Interfaces (API). We use OpenCV, an open-source BSD-licensed library of programming functions that allows users to access a variety of open-source Scientific Python packages, including numerous computer vision algorithms [19].

The OpenCV application is mostly composed of two stages [32].

The first step is feature engineering, which is mostly based on a code implementation to determine the optimal method to represent data in this case, data derived from an image for use in machine learning algorithms.

The second step is feature extraction, which includes Linear Blend Threshold, Binarization, Bounding Box generation, particle feature extraction, and size and morphology classification. The process of overlaying a foreground image with transparency (typically the fourth channel of an image) over a background image is known as Linear Blend Threshold [12,5]. This transparency mask, also known as the alpha mask, is useful in the Binarization process, in which we apply Otsu's thresholding to convert the sample image to black and white.

3.3.4 Image processing workflow

Importing libraries

Different libraries make it easier for us to continue working on the sample photos' image processing. For image processing and computer vision, OpenCV is a great tool. It's an open-source library for tasks including face recognition, objection detection, landmark identification, and much more.

NumPy is a Python module that helps us to use arrays. Numpy provides functions for working with matrices, fourier transforms, and linear algebra. Matplotlib is a Python library that allows you to create static, animated, and interactive visualisations. Matplotlib makes simple things simple and difficult things possible. Seaborn is a matplotlib-based Python data visualisation library [22,17,8]. It offers a high-level interface for creating visually appealing and informative statistical graphics.

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
import sys
import seaborn as sns
```

While OpenCV was designed for full-scale applications and can be used within functionally rich UI frameworks or without any UI at all, it is sometimes necessary to try functionality quickly and visualize the results. The HighGUI module was created for this purpose.
It provides a simple interface to:

i. Create and manipulate windows capable of displaying images and "remembering" their contents (no need to handle repaint events from OS).
ii. Add slider to the windows to handle simple keyboard commands and mouse events.

We have added sliders and drop down menu to make it simpler and user friendly.

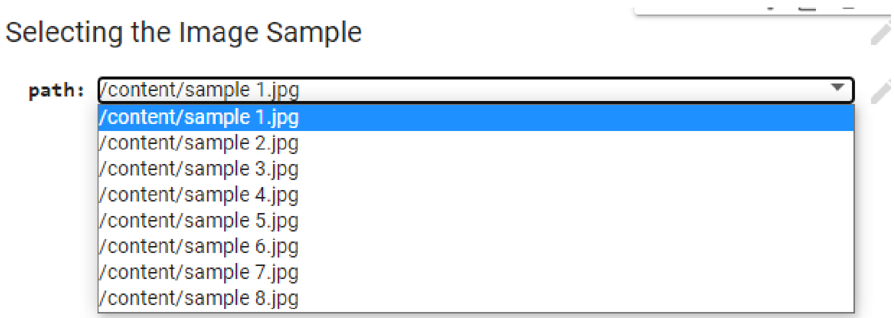


Figure 3.9 Drop down menu

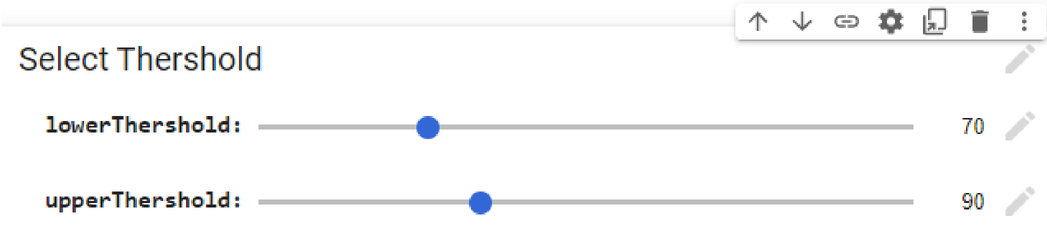


Figure 3.10 Slider

Read, Resize and Show Images

Then the images are read, resized/scaled and shown using OpenCV. Scaling an image means changing its dimensions, which can be only its width, only its height, or both.

The imread() function is used to read an image in Python using OpenCV. Depending on the number of color channels in the image, imread() outputs a 2D or 3D matrix. Imshow() in matplotlib makes a picture from a 2-dimensional numpy array. Every element of the array will be represented by a square in the image. The value of the relevant array element and the color map used by imshow() define the color of each square[22.24.27].
We can specify the width and height of a Figureure in unit inches using the Figuresize attribute. The Figuresize property is a Figureure function parameter ().

```
#Reading the image
#@title Selecting the Image Sample {run: 'auto'}

path = "/content/sample 1.jpg" #@param ["/content/sample 1.jpg
","/content/sample 2.jpg","/content/sample 3.jpg","/content/sa
mple 4.jpg","/content/sample 5.jpg","/content/sample 6.jpg","/
content/sample 7.jpg","/content/sample 8.jpg"]
image  = cv2.imread(path)
plt.Figureure(Figuresize=(8,8)
plt.imshow(image)
```

Figure 3.11 Read, Resize and Show image in OpenCV-Python

Grey scaling and setting blur

A grayscale image is one in which each pixel indicates the quantity of light or just provides information about light intensity. It's a single-dimensional graphic with simply varied shades of grey.

Grey scaling is the process of transforming an image to shades of grey from various color spaces such as RGB, CMYK, HSV, and so on.

Greyscale representations are frequently employed for extracting descriptors rather than operating directly on color images since they simplify the technique and reduce computational requirements [20,22].

Importance of grey scaling:

i. Dimension is reduced: In RGB photographs, for example, there are three color channels and three dimensions, whereas grayscale images are single-dimensional.
ii. Model complexity is reduced: Consider using RGB images of 10x10x3 pixels to train neural articles. There will be 300 input nodes in the input layer. For grayscale photos, however, the same neural network will only require 100 input nodes.
iii. Helps in other algorithms to function: Many algorithms, for example, are tailored to function solely with grayscale photos. The pre-implemented Canny edge detection function in the OpenCV library only works on Grayscale images.

The image is blurred by using a low-pass filter kernel to convolve it. It can be used to reduce noise. It really removes high frequency material from the image (such as noise and edges). This procedure blurs the margins a little (there are other blurring techniques that just don't blur the edges).

A Gaussian kernel is utilized in the Gaussian blurring approach. It's done with the cv2.GaussianBlur function (). We must define the kernel's width and height, which must be positive and odd. When it comes to reducing Gaussian noise from the image, Gaussian blurring is extremely successful [16,19].

```
#Converting the colored image into grey and setting blur
#@title Select Blur Level{run: 'auto'}
blurLevel = 3 #@param {type:"slider", min:1, max:9, step:2}
dst = cv2.GaussianBlur(image,(blurLevel,blurLevel),cv2.BORDER_
DEFAULT)
gray = cv2.cvtColor(dst, cv2.COLOR_BGR2GRAY)

plt.Figureure(Figuresize=(8,8))
plt.imshow(gray,cmap="gray")
```

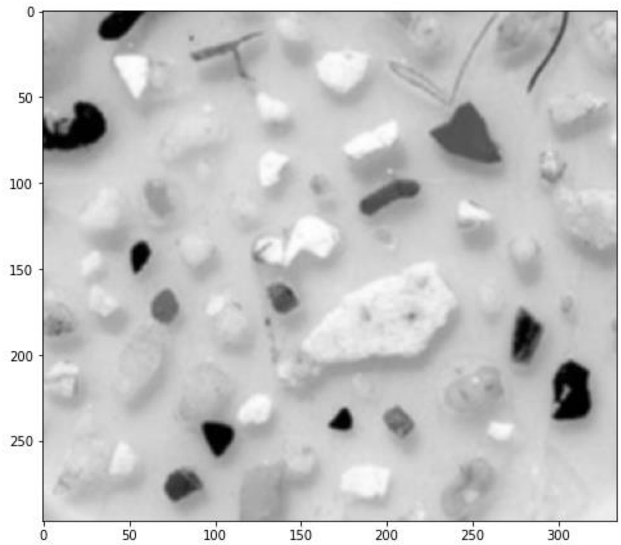
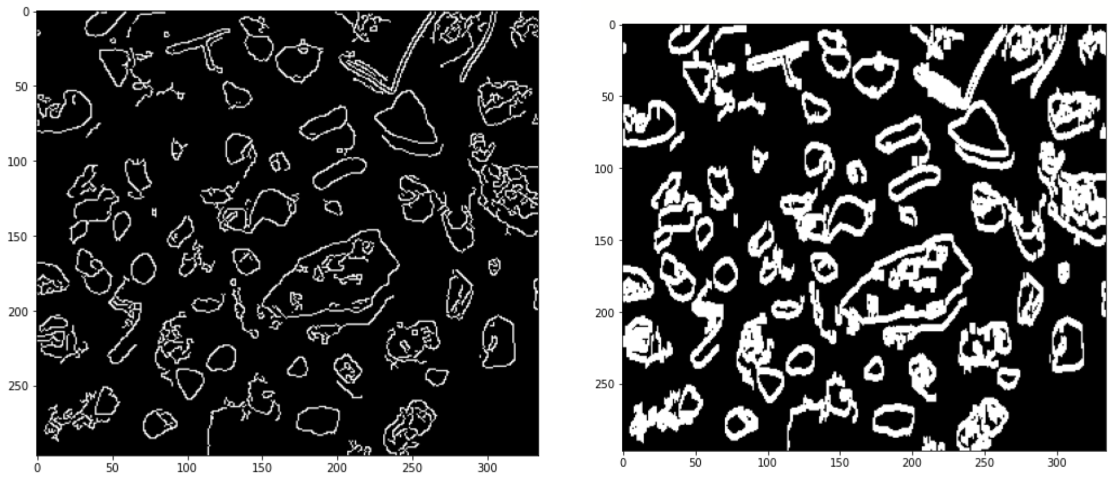


Figure 3.12 Grey scaled image

Detecting the edges of the microplastic particles

A prominent edge detection algorithm is Canny Edge Detection. John F. Canny came up with the idea. This function determines which edges are genuine and which are not. We will require two threshold values, minimum value and maximum value, for this. Any edges with an intensity gradient more than maximum value are certain to be edges, whereas those with an intensity gradient less than minimum value are certain to be non-edges, and should be rejected [40]. Based on their connectedness, those who fall between these two thresholds are classed as edges or non-edges. They are considered as part of edges if they are related to "sure-edge" pixels. Otherwise, they are eliminated as well [41].

```
lowerThershold = 40 #@param {type: 'slider', min:10,max:250, step: 10 }
upperThershold = 50 #@param {type: 'slider', min:10,max:250, step: 10 }
canny = cv2.Canny(gray, lowerThershold,upperThershold,100, 3)
plt.Figureure(Figuresize=(8,8))
plt.imshow(canny,cmap="gray")
#making the edges more thinker and visible
dilated = cv2.dilate(canny, (4,4), iterations = 4)
plt.Figureure(Figuresize=(8,8))
plt.imshow(dilated,cmap="gray")
```



(a) (b)

Figure 3.13 (a) Edge detection; (b) Dilation of edges

Drawing contour lines over the original image

Contours are simply defined as a curve that connects all continuous points (along a boundary) that are of the same hue or intensity. The contours are an effective tool for form analysis as well as object tracking. Binary images are used for higher accuracy. We use thresholding and canny edge detection before finding contours [41].

Finding contours in OpenCV is similar to detecting a white object against a black background. So keep in mind that the thing you're looking for should be white and the background should be dark.

The cv2.findContours() function takes three arguments: source picture, contour retrieval mode, and contour approximation method. It also generates a changed image, as well as the contours and hierarchy [42].

```
(cnt, heirachy)  = cv2.findContours(dilated, cv2.RETR_EXTERNAL
,cv2.CHAIN_APPROX_NONE)

# we have to convert BGR to RGB and then draw the image contou
rs
rgb = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
cv2.drawContours(rgb, cnt,-1 ,(0,255,0),4)
plt.Figureure(Figuresize=(8,6))
plt.imshow(rgb)
```

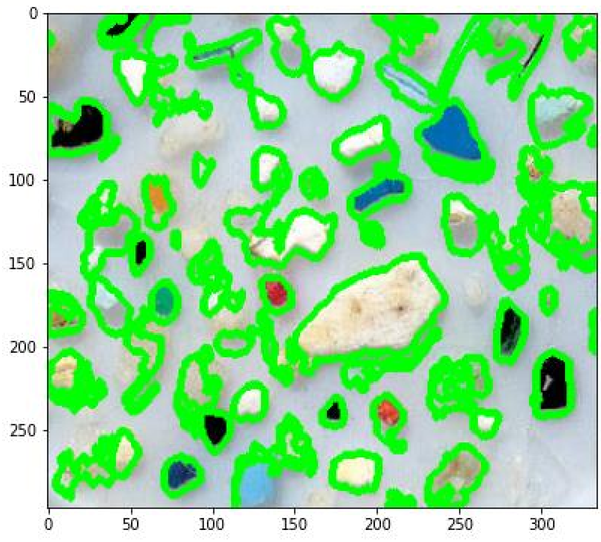


Figure 3.14 Drawing contour lines over the original image

Quantification of microplastic particles present in the sample image

Plastic pellets, often known as nurdles or beads, are shaped and sized like lentils (2-5 mm diameter). Polymeric producers and recycling facilities produce them, which are then delivered to facilities where they are melted and molded into the final shape of the plastic product.

Tiny bits of plastic that break away from bigger pieces of plastic are called fragments. Cutlery, lids, and single-use goods are all common examples. The sun's ultraviolet radiation breaks down these shards further into smaller pieces [42,43].

Fibers are responsible for 71% of all microplastic pollution in the Great Lakes. Fleece garments, cigarette butts and diapers are all sources of microfibers. Microfibers enter our lakes in a variety of ways, including through our own washing machines. A single wash of a fleece jacket can release 2,000 microfibers into our rivers. According to Patagonia-funded research, 40% of microfibers are not cleaned out at wastewater treatment plants. As a result, sewage drains may become plugged. Fleece microfibers, unlike cotton or wool, are not biodegradable [4].

Figure 3.15 Different types of microplastic particles (Source: [4])

Firstly we initialize the number of pellets, fragments and fibers as zero. Then a ‘for loop’ is applied to count the number of each individual type of microplastic particles. The total number of microplastic particles detected in the sample image is stored in cnt variable. If-else statement is used to check if the conditions we provide are true or false. We make use of the function cv2.approxPolyDP to differentiate pellets, fragments and fibers. If the len(approx) is equal to 2 it is taken as fiber. Else-if the len(approx) is 8 it is counted as a pellet. If both the above mentioned conditions are false then the particle detected is counted as a fragment.

```python
#Circular
pellet = 0

#Unstructured
fragment = 0

#line
fiber = 0

for  cn in cnt:
  peri = cv2.arcLength(cn, True)
  approx = cv2.approxPolyDP(cn, 0.04 * peri, True)
  x,y,w,h = cv2.boundingRect(cn)

  if(len(approx) == 2):
    fiber = fiber + 1
  elif(len(approx) == 8 ):
    pallet = pallet + 1
  else:
    midX = (approx[0][0][0] + approx[-1][0][0]) / 2
    midY = (approx[0][0][1]+ approx[-1][0][1]) / 2
    sizeX = image.shape[0]
    sizeY = image.shape[1]
    if(midX < sizeX and midY < sizeY):
      (b, g, r) = image[int(midX),int(midY)]
      if( b == 0 and g == 0 and r ==0):
        fiber = fiber + 1
      else:
        fragment = fragment + 1
    else:
      fragment = fragment + 1

print("Number of fragment: ",fragment)
```

```
print("Number of fiber: ", fiber)
print("Number of pellet: ",pallet)
```

```
Number of fragment:  57
Number of fiber:  2
Number of pellet:  3
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
```

```
Total number of micor_plactics:  62
```

Graphical representation of the result

Matplotlib is one of the most widely used plotting libraries in Python. It's an open-source, cross-platform tool for creating 2D charts from array data. It is commonly used for data visualisation and is represented by a variety of graphs.

A graph is made up of the following components.

Figureure: A complete Figureure that may contain one or more axes (plots). A Figureure can be thought of as a canvas which holds plots.

Axes: A Figureure can also have multiple Axes. It is made up of 2 or 3 (in 3D) Axis objects. Each axes has a title, an x-label, and a y-label.

Axis: Axes are indeed the number of line-like objects that generate the graph limits.

An artist is everything we see on the graph, such as text objects, line2d objects, and collection objects. Most artists are associated with axes.

One of the most used graphs is the bar graph, which is used to show data related to categorical variables. Categorical variables, values, and colour are the three arguments of the bar() function [33,37].

```
#X-values
types = ["Fragment", "Fiber", "Pellet"]

# creating the bar plot
Figure = plt.Figureure(Figuresize = (10,5))

# creating the bar plot
plt.bar( types,[fragment,fiber,pallet], color ='sky blue',
        width = 0.6)

plt.xlabel("Micro-plastics")
plt.ylabel("No. of plastics detected")
plt.title("Various micro-plastics")
plt.show()
```

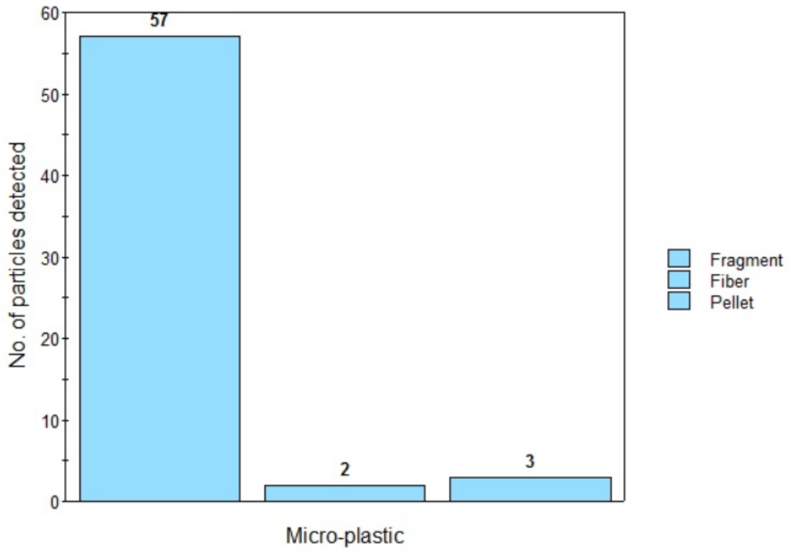
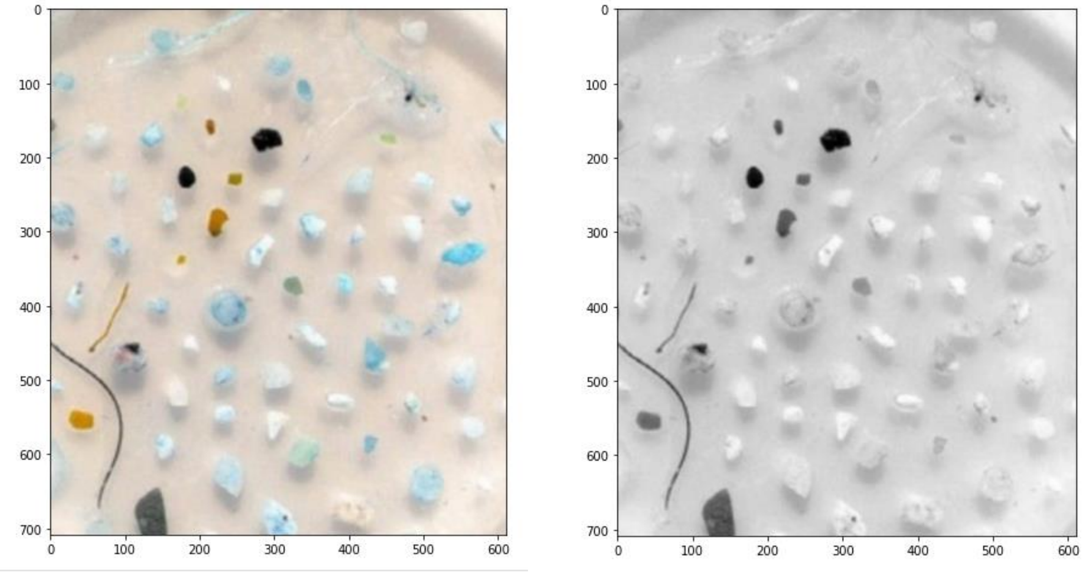


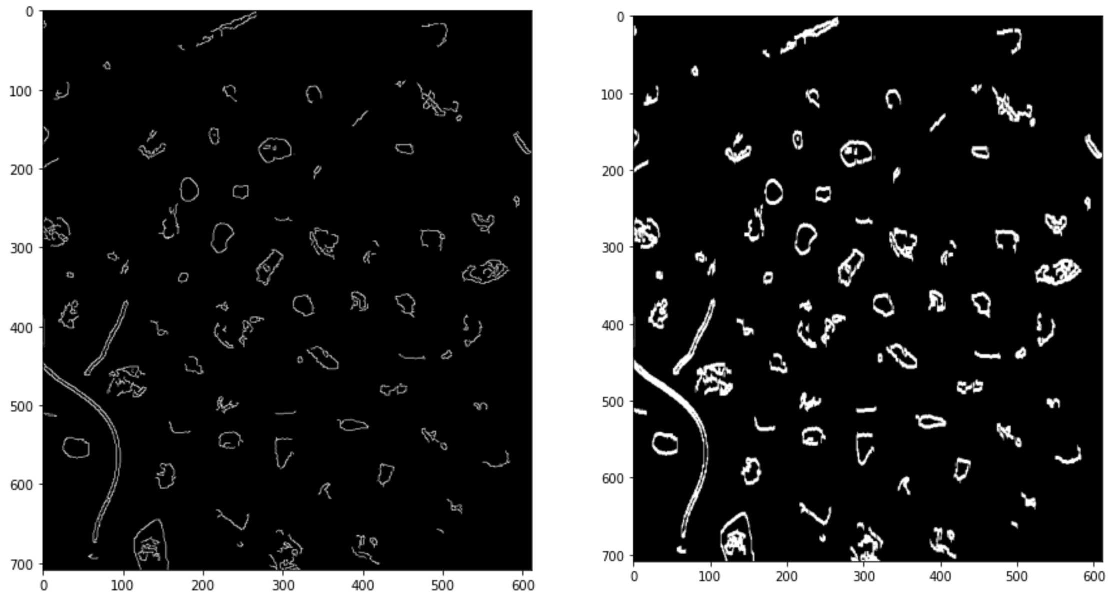
Figure 3.16 Graphical representation of microplastic counts

Sample 2



(a) **(b)**

Figure 3.17 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.18 (a) Edge detection; (b) Dilation of edges

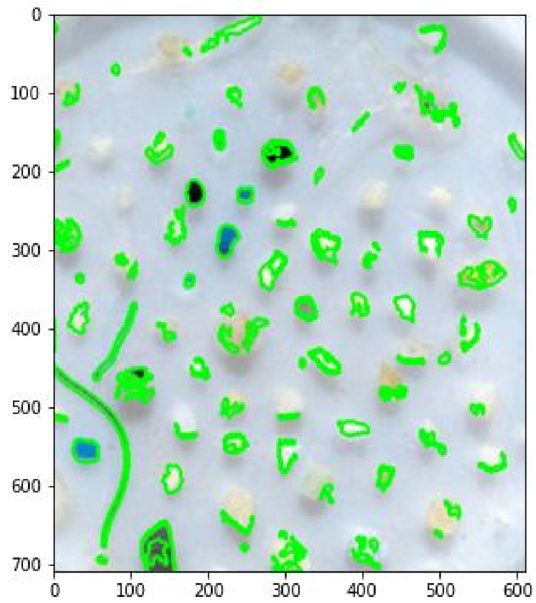
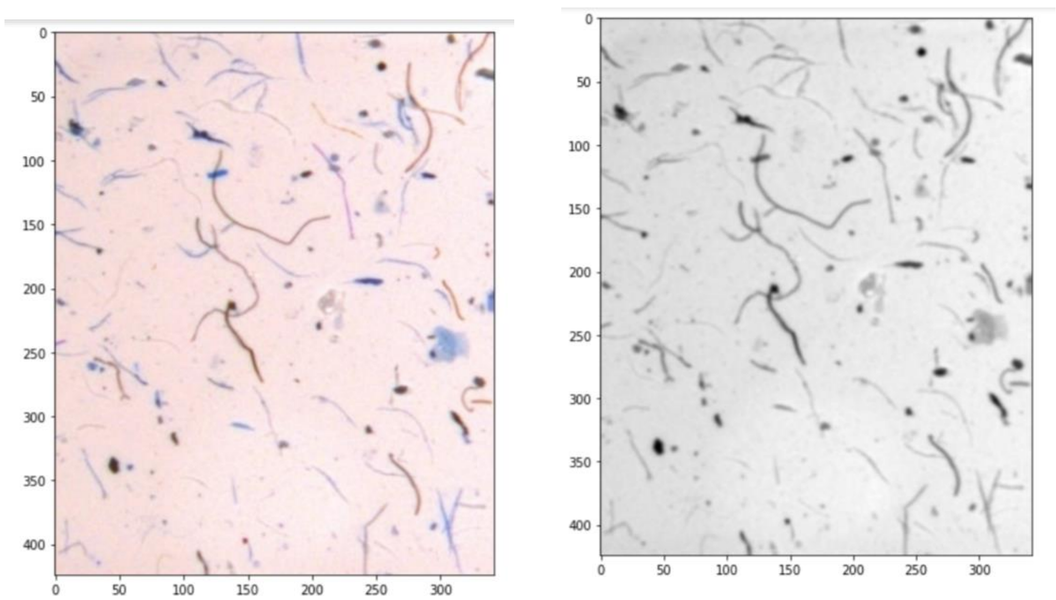


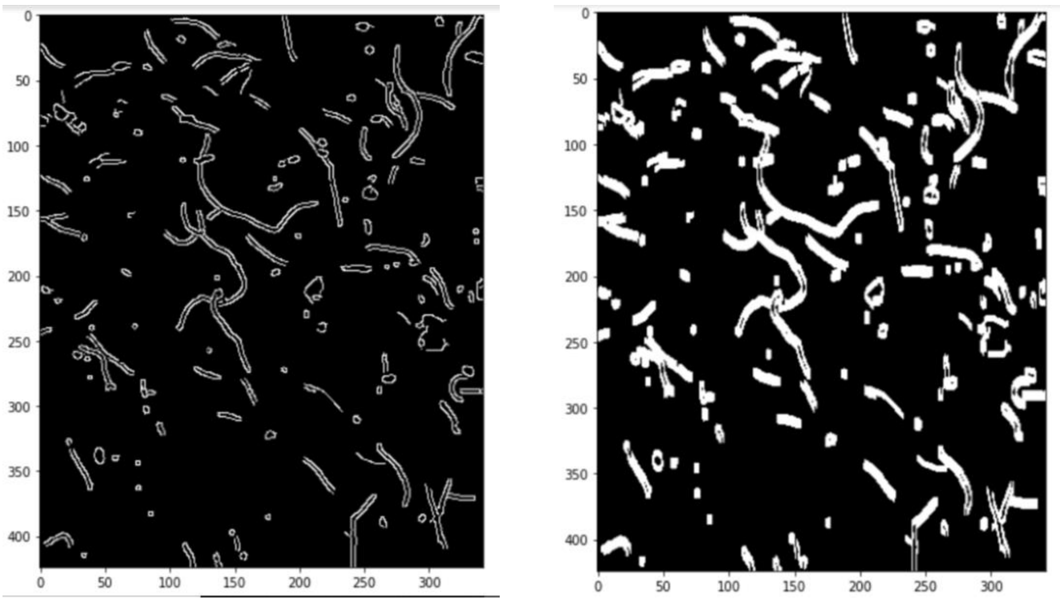
Figure 3.19 Drawing contour lines over the original image

Sample 3



(a) **(b)**

Figure 3.20 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.21 (a) Edge detection; (b) Dilation of edges

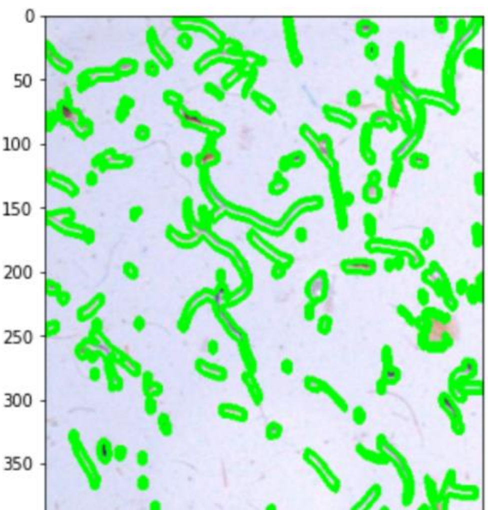
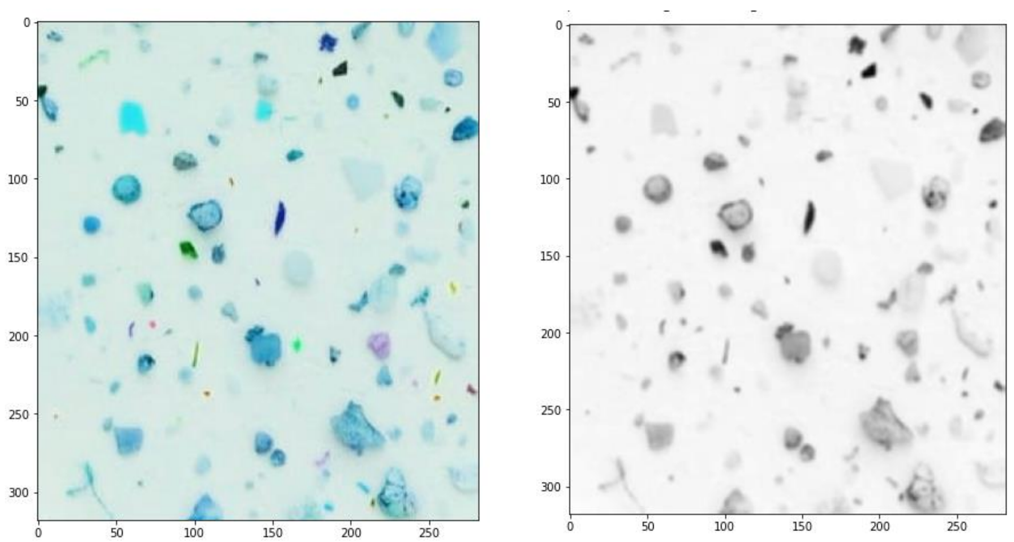


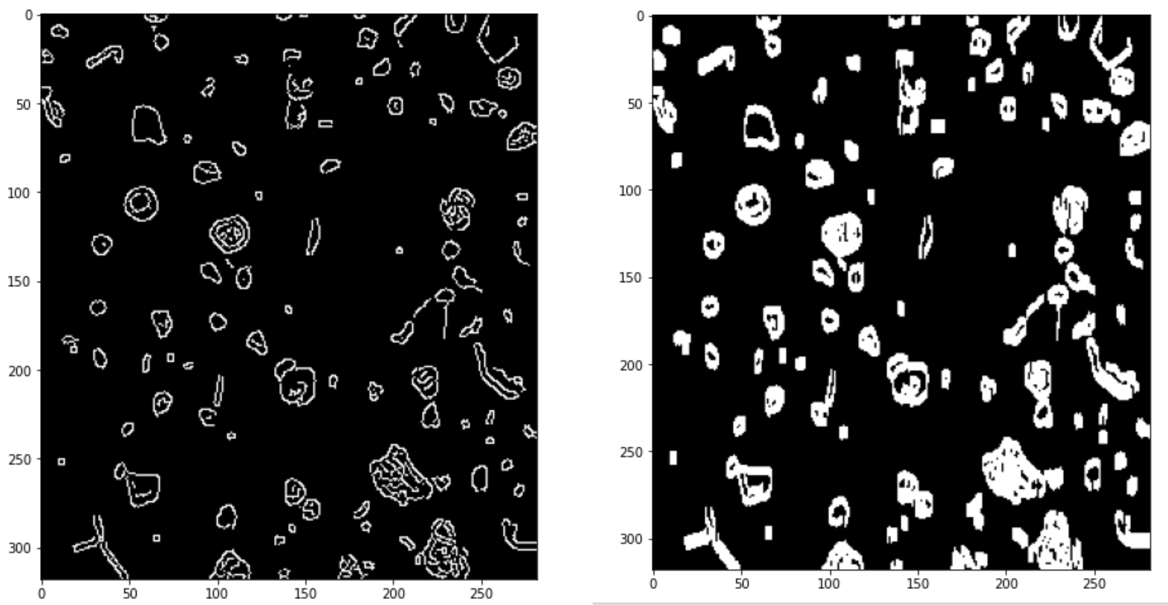
Figure 3.22 Drawing contour lines over the original image

Sample 4



(a) **(b)**

Figure 3.23 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.24 (a) Edge detection; (b) Dilation of edges

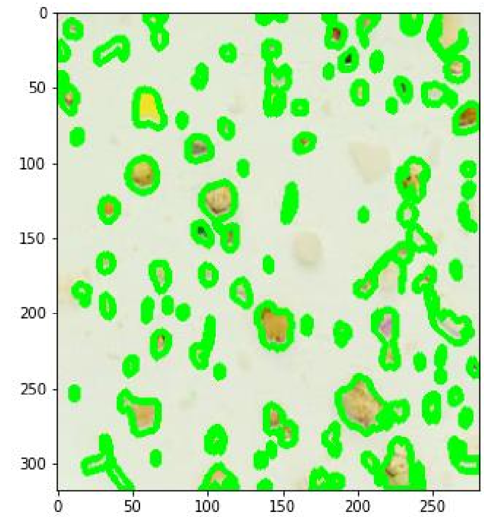
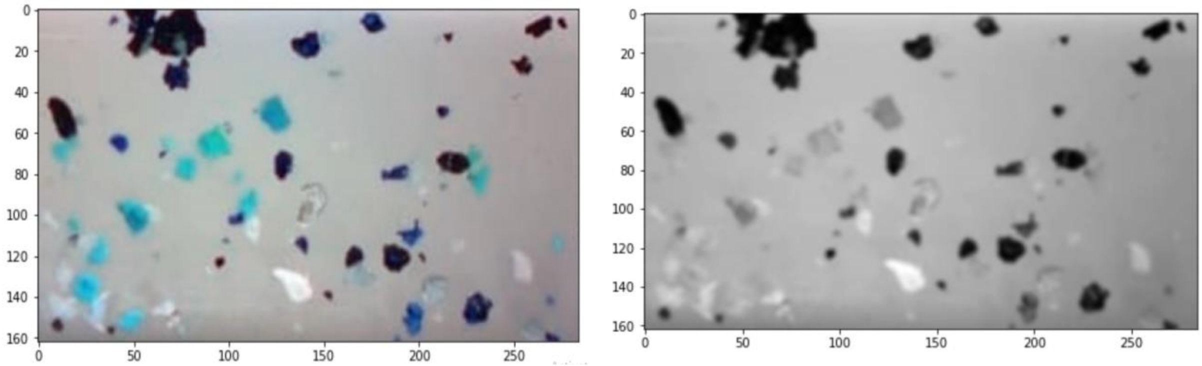


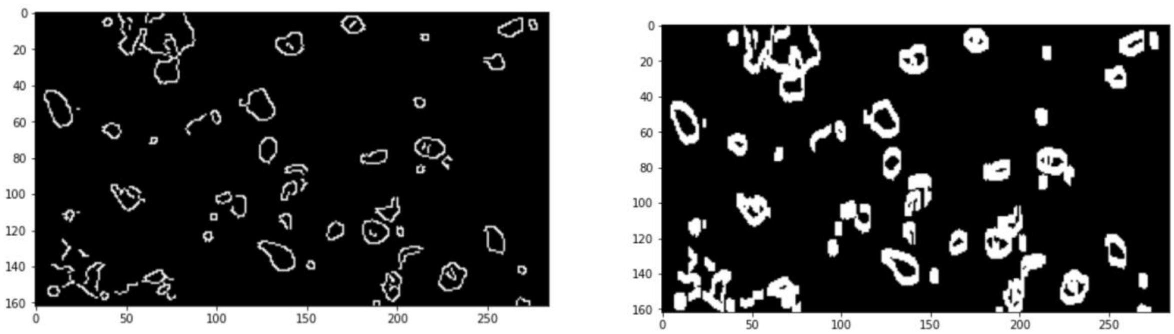
Figure 3.25 Drawing contour lines over the original image

Sample 5



(a) **(b)**

Figure 3.26 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.27 (a) Edge detection; (b) Dilation of edges

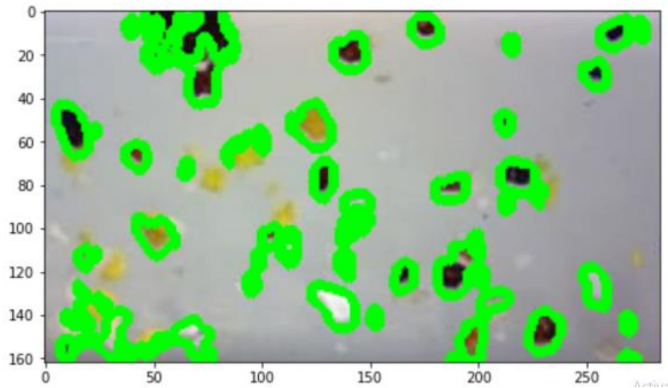
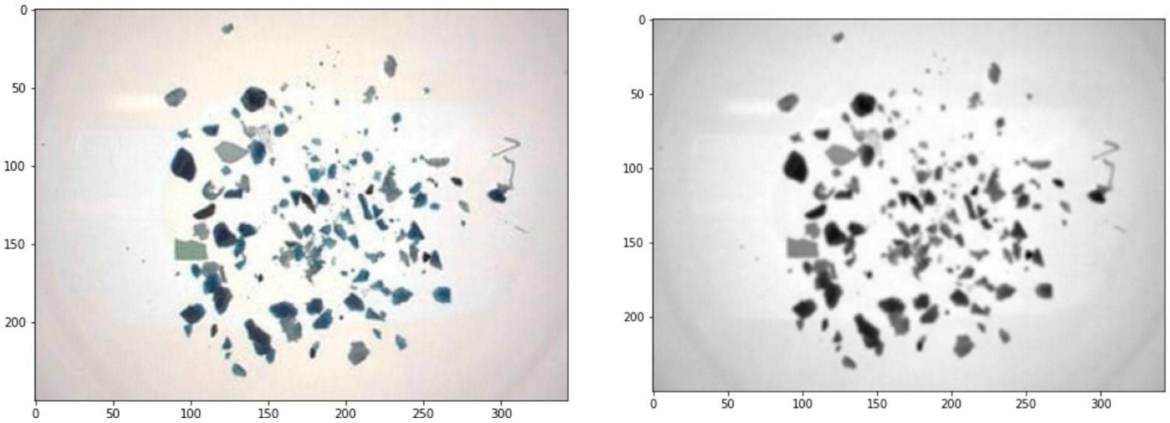


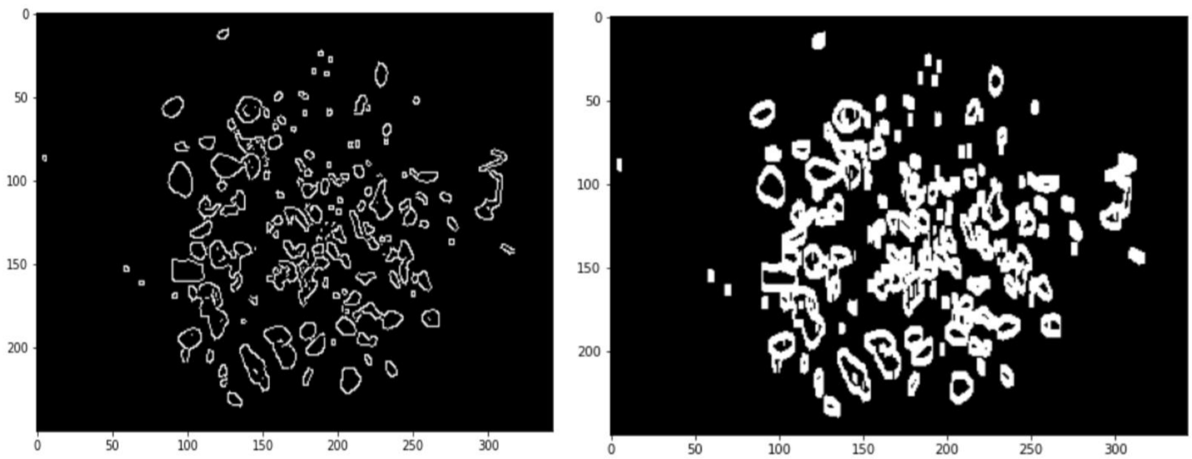
Figure 3.28 Drawing contour lines over the original image

Sample 6



(a) **(b)**

Figure 3.29 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.30 (a) Edge detection; (b) Dilation of edges

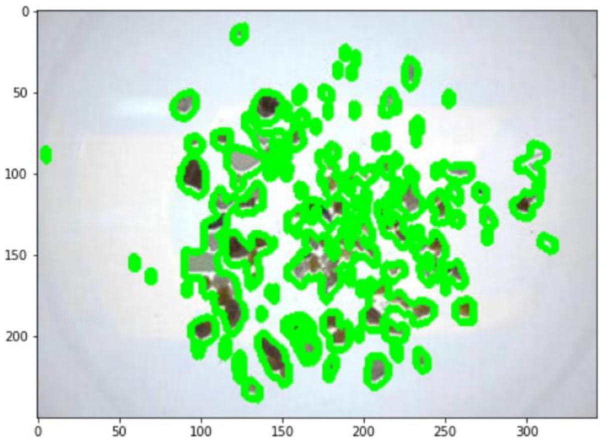
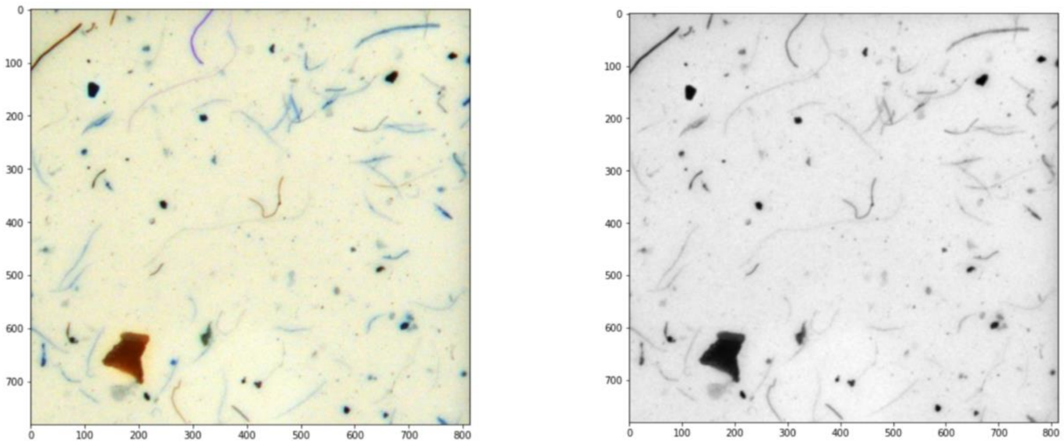


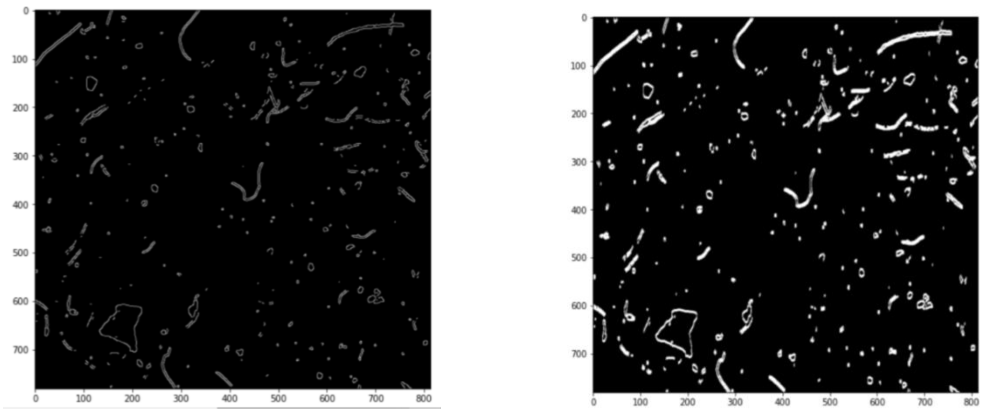
Figure 3.31 Drawing contour lines over the original image

Sample 7



(a) **(b)**

Figure 3.32 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.33 (a) Edge detection; (b) Dilation of edges

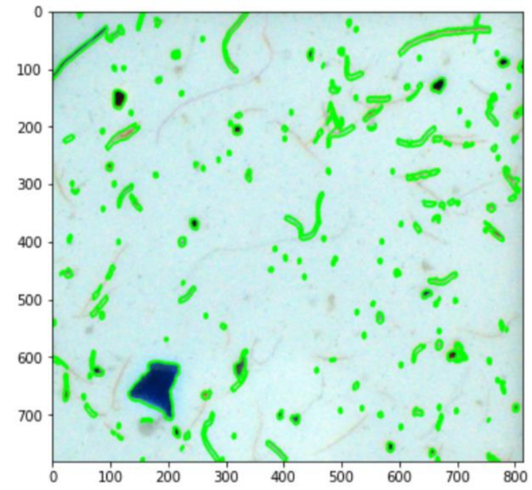
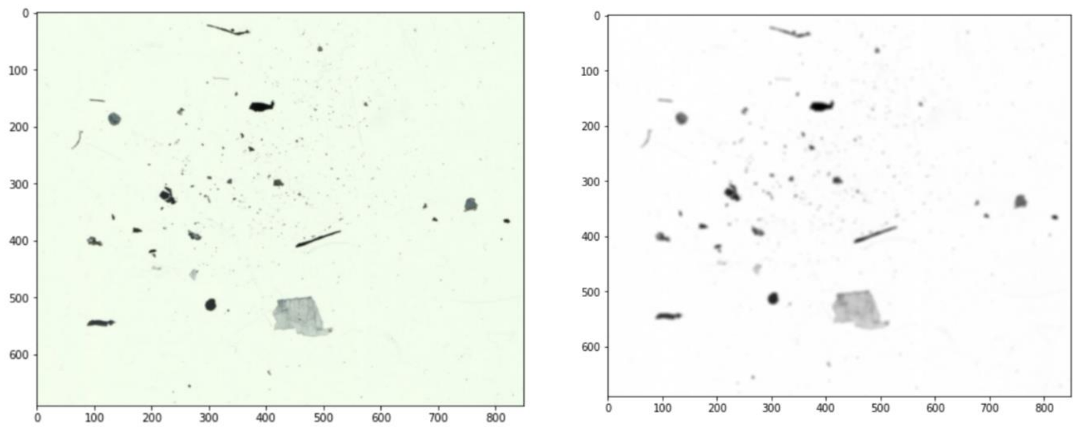


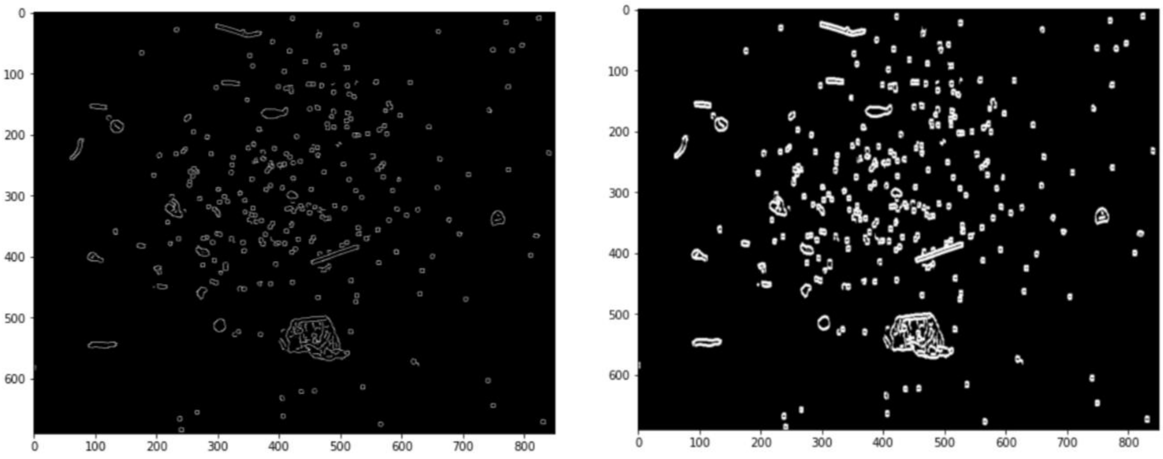
Figure 3.34 Drawing contour lines over the original image

Sample 8



(a) **(b)**

Figure 3.35 (a) Read, Resize and Show image in OpenCV-Python; (b) Grey scaled image



(a) **(b)**

Figure 3.36 (a) Edge detection; (b) Dilation of edges

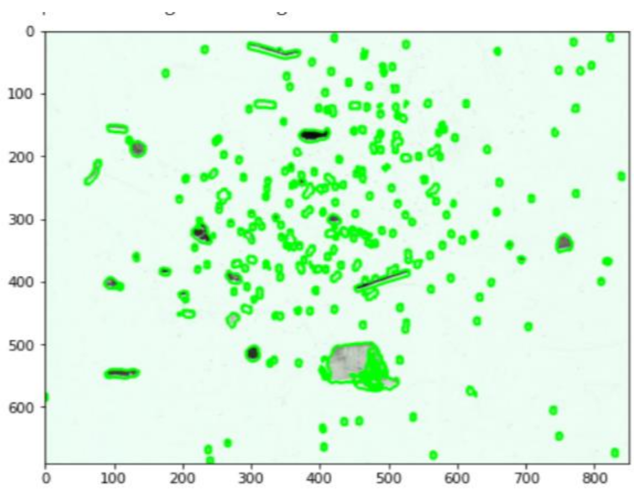


Figure 3.37 Drawing contour lines over the original image

CHAPTER 4

RESULTS

4.1 GENERAL

In this section, we will demonstrate and discuss the results of image processing of the sample images in OpenCV-python. We will also discuss the benefits of using digital image processing and how automatic generation of particle counts is easier and faster using image processing technique than the manual lab processes.

4.2 RESULTS

The main objective of our project was to employ image processing technique to detect and quantify the microplastic particles present in the water sample images. For greater accuracy of particle counts, it is essential to have images of great quality. For our project, since we couldn't take sample images on our own and had to take the sample images from online sources, the image quality aren't up to the mark. Due to that there are few deviations in the counts of microplastic particles in each sample.

Since the particles are three-dimensional particles, they adopt various spatial conformations when placed on a flat surface. For example, rolling fibers are sometimes incorrectly classified as pellets because they look circular like pellets when they are placed in that way. Also the pellets that are white in color are difficult to detect as they look similar to the white background and are sometimes neglected.

Depending on the sample images used, the algorithm sometimes shows the count more than the actual particle count present in the image and sometimes shows less count then the actual number of particles present in the sample images. Overestimation could occur if the image had a very high resolution and a dust grain was sometimes confused with a particle; underestimation could occur if the resolution was low and the particles were too close together. These differences, however, are within the acceptable range for monitoring studies.

The particle counting process has produced the most satisfactory results. It is important to emphasize that by automating this phase, human errors are avoided, which can occur due to tiredness due to the prolonged process time of the images required in the manual particle count.

The bar graph for each sample image shows the total number of microplastic particles subdivided in different morphologies (fragments, fibers and pellets).

Microplastic particles detected in sample image 1:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  57
Number of fiber:  2
Number of pallet:  3
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  62
```

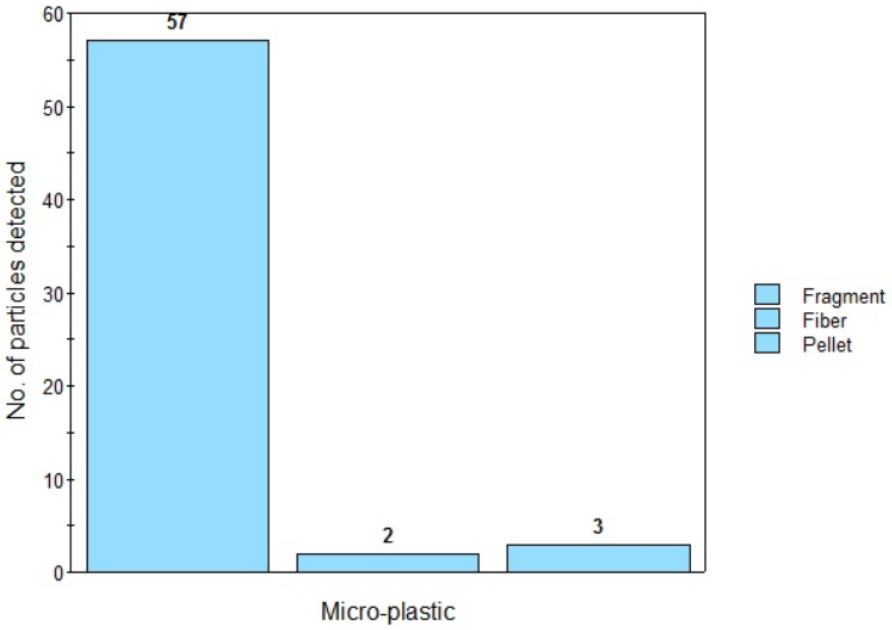


Figure 4.1 Microplastic particles detected in sample image 1

Microplastic particles detected in sample image 2:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  92
Number of fiber:  5
Number of pallet:  9

#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  106
```

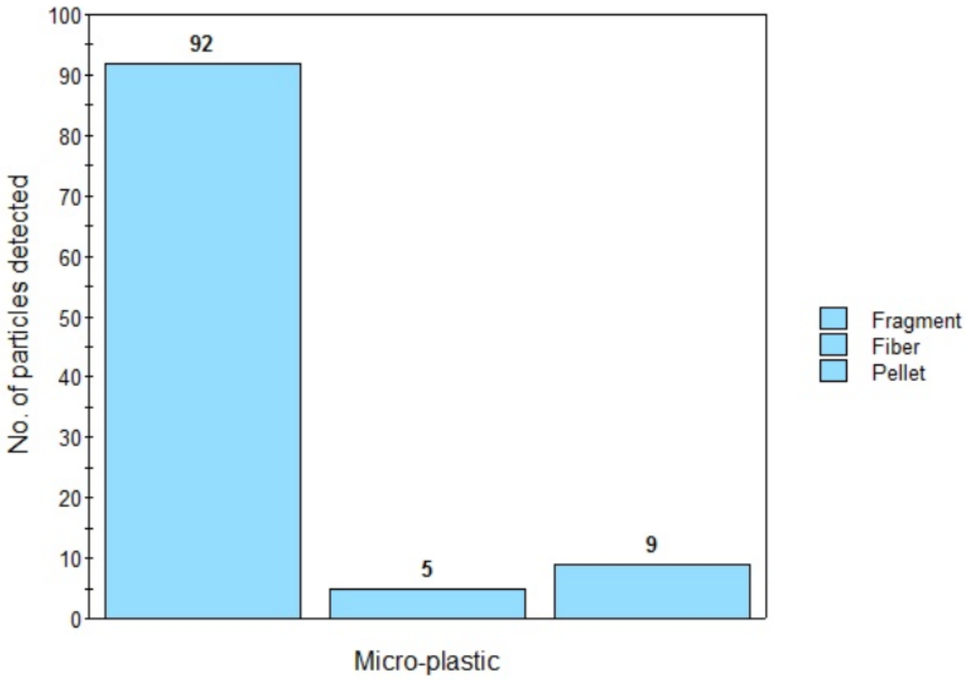


Figure 4.2 Microplastic particles detected in sample image 2

Microplastic particles detected in sample image 3:

```
Number of fragment:  4
Number of fiber:  67
Number of pallet:  2
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  73
```

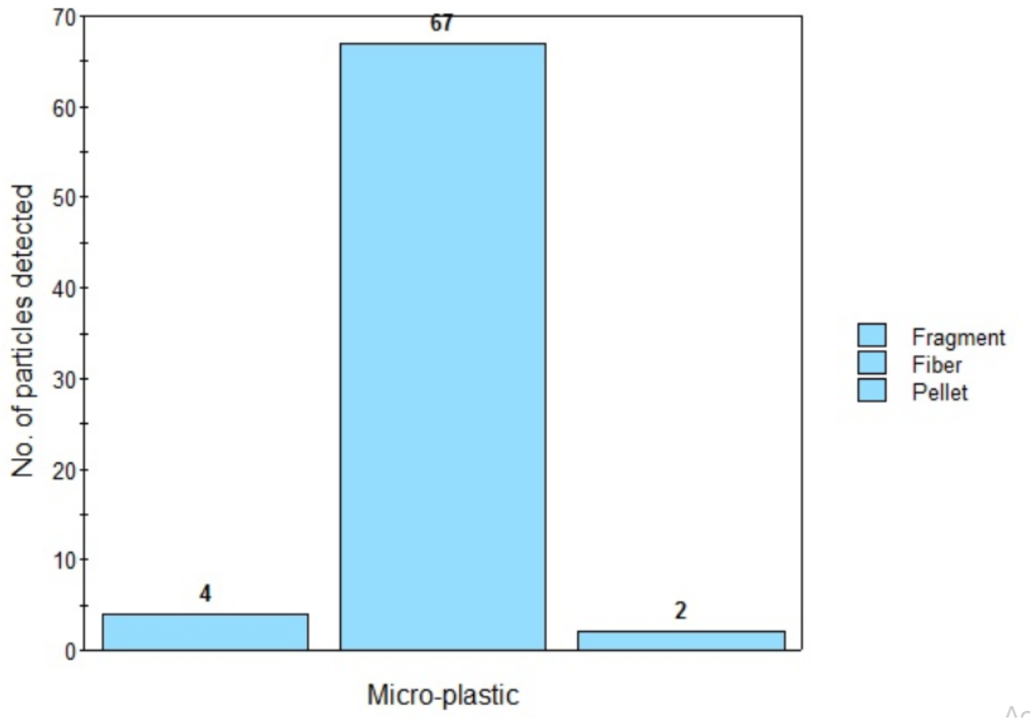


Figure 4.3 Microplastic particles detected in sample image 3

Microplastic particles detected in sample image 4:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
```

```
Number of fragment:  86
Number of fiber:  1
Number of pallet:  3
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  90
```

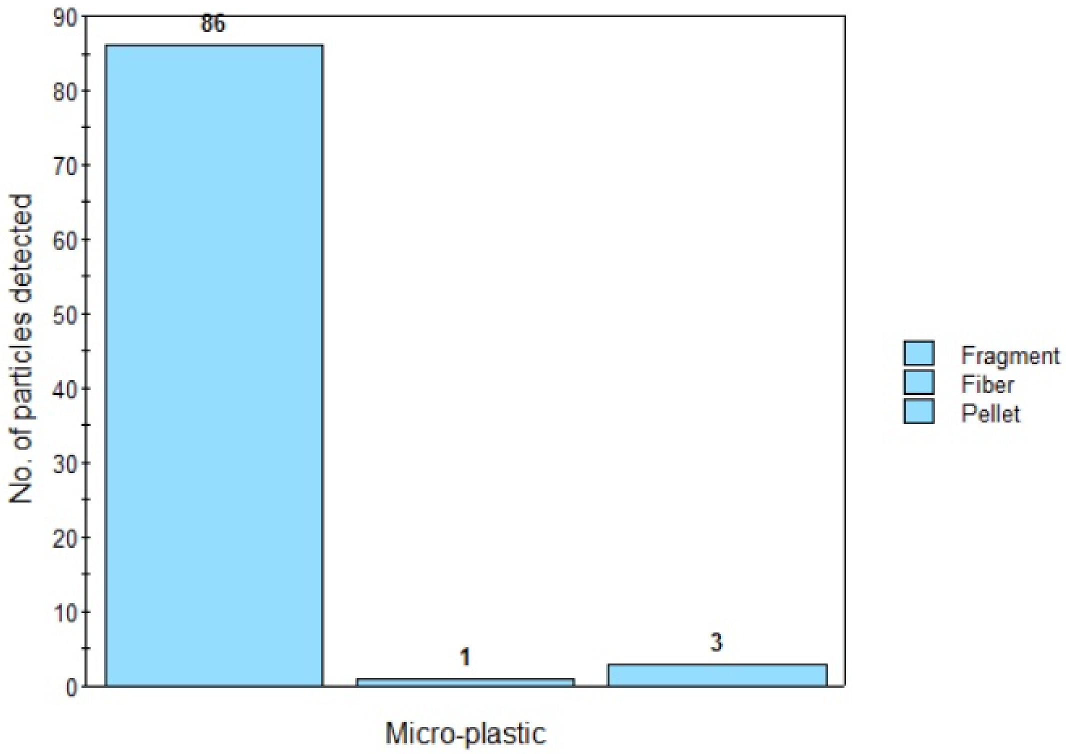


Figure 4.4 Microplastic particles detected in sample image 4

Microplastic particles detected in sample image 5:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  43
Number of fiber:  0
Number of pallet:  3
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  46
```

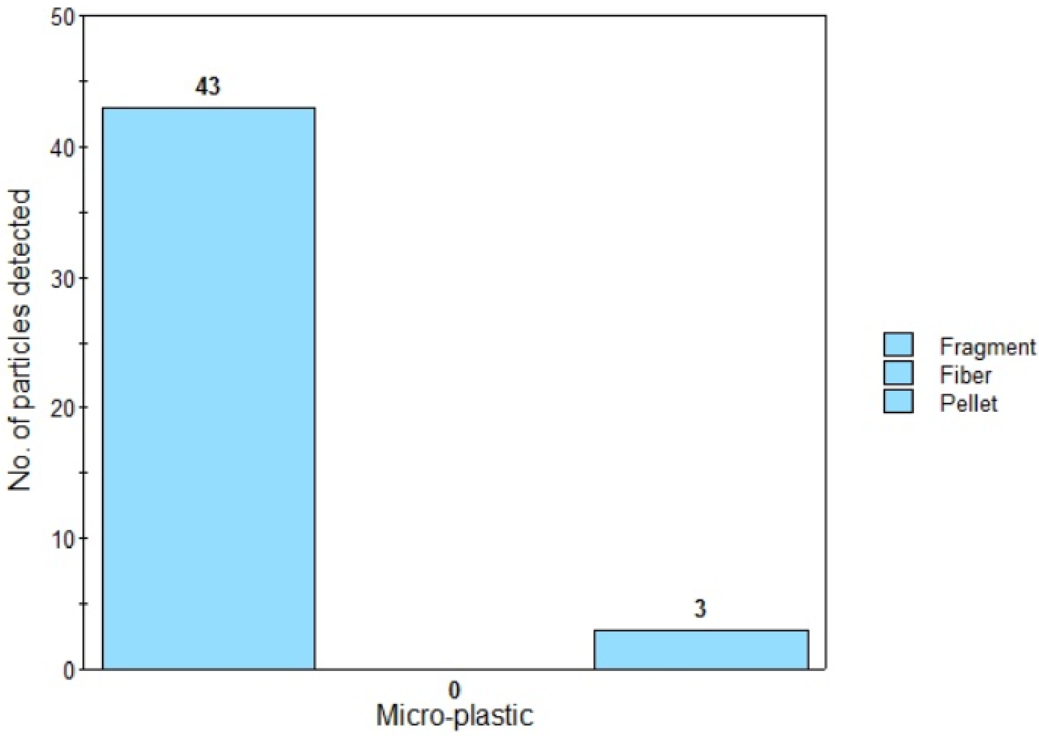


Figure 4.5 Microplastic particles detected in sample image 5

Microplastic particles detected in sample image 6:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  63
Number of fiber:  2
Number of pallet: 2
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
```

```
Total number of micor_plactics:  67
```

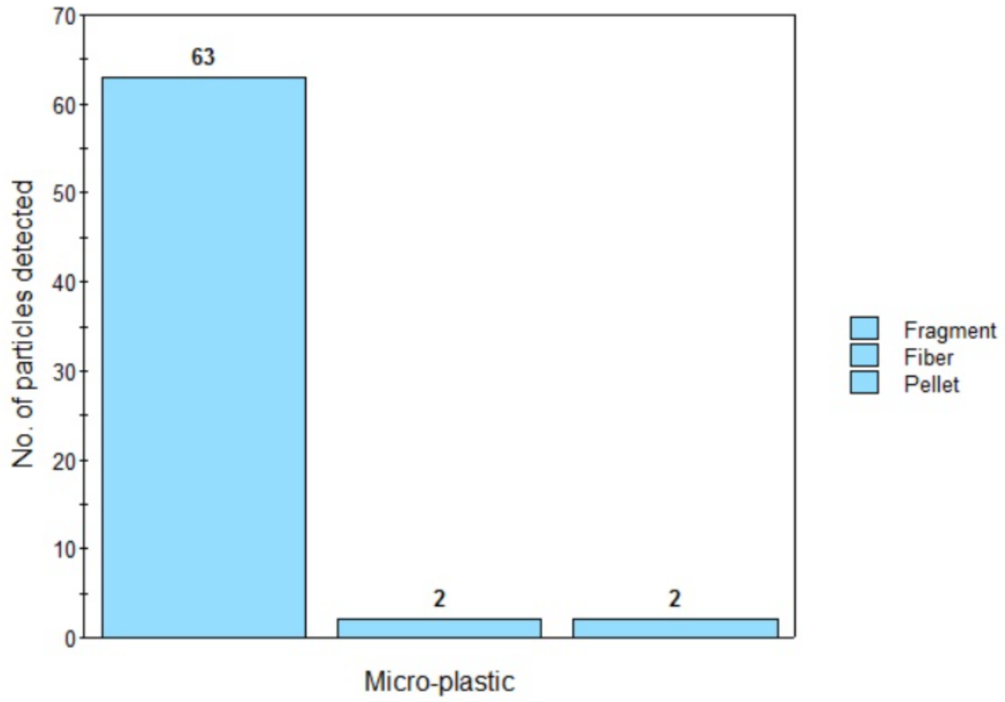


Figure 4.6 Microplastic particles detected in sample image 6

Microplastic particles detected in sample image 7:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  23
Number of fiber:  73
Number of pallet: 2
```

```
#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  98
```

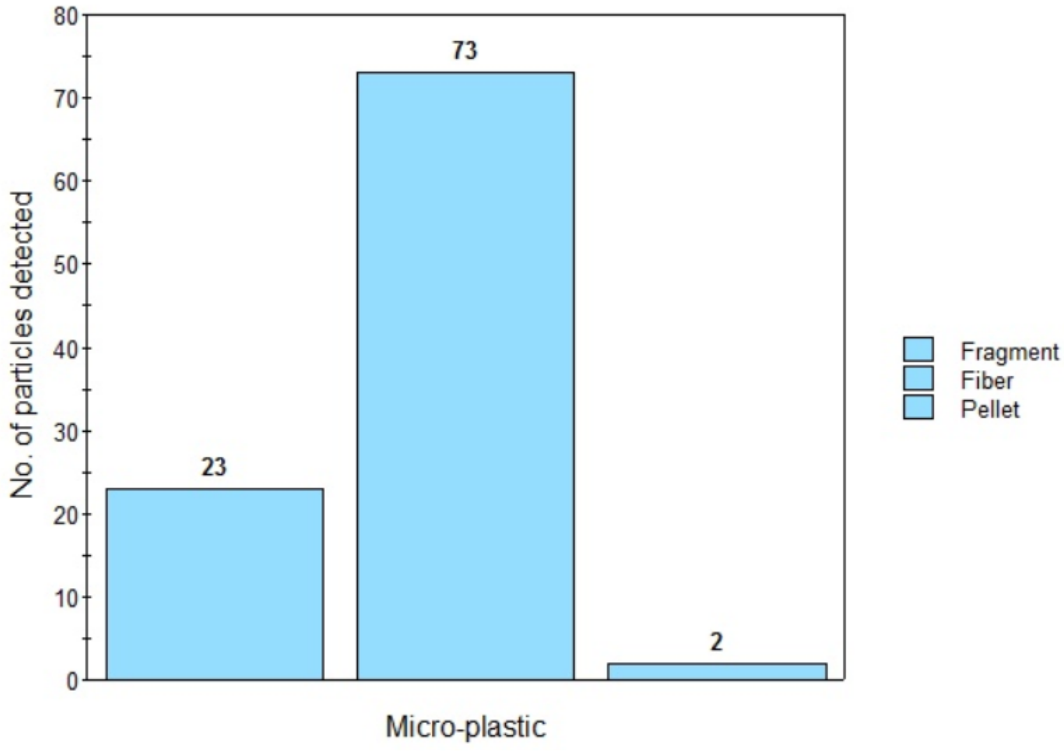


Figure 4.7 Microplastic particles detected in sample image 7

Microplastic particles detected in sample image 8:

```
print("Number of fragment: ",fragment)
print("Number of fiber: ", fiber)
print("Number of pallet: ",pallet)
Number of fragment:  194
Number of fiber:  4
Number of pallet: 11

#To print the number of micro-plastics:
print("Total number of micor_plactics: ",len(cnt))
Total number of micor_plactics:  209
```

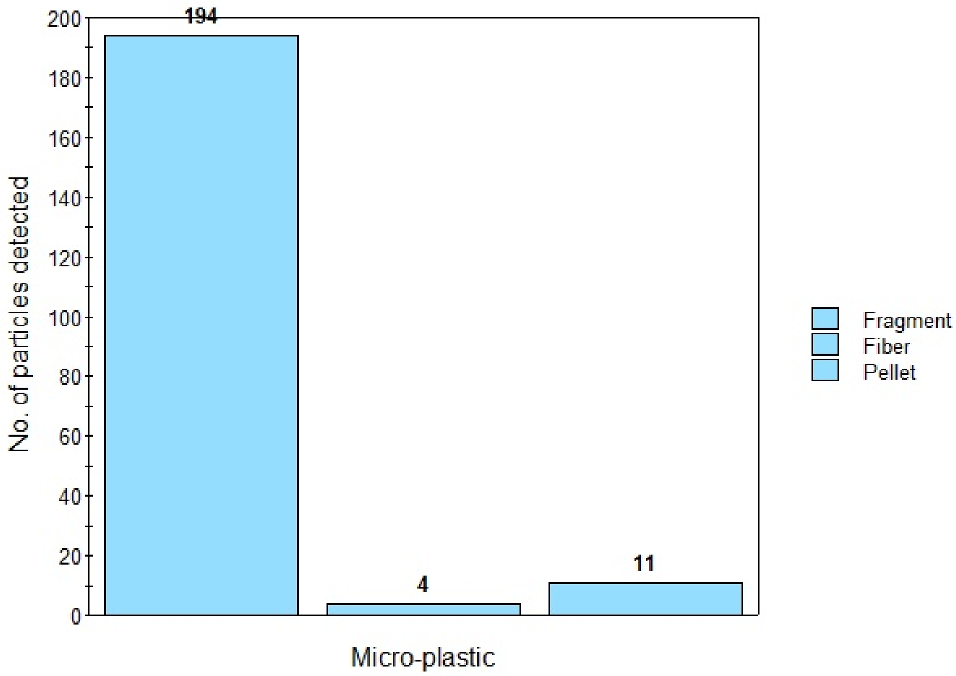


Figure 4.8 Microplastic particles detected in sample image 8

Table 4.1 Particle counts in each sample image

Sample	Fragments	Fibers	Pellets	Total particles
1	57	2	3	62
2	92	5	9	106
3	4	67	2	73
4	86	1	3	90
5	43	0	3	46
6	63	2	2	67
7	23	73	2	98
8	194	4	11	209

4.3 INFERENCE

Overall, the MPs' automatic counting and categorization via OpenCV-python produced promising results that were significantly comparable to the outcomes of human experts. The obtained results show that the differences revealed were within acceptable error range for monitoring studies [21].

It is important to emphasize that automatic particle counting eliminates human errors, which can occur due to exhaustion due to long process time of the images required in manual particle counting.

However, it is worth noting that in order to achieve satisfactory results, particles must be precisely placed over the background, separated one by one manually to prevent overlapping. This process does take time, but it is also a procedure that should be performed in the traditional counting of particles underneath a microscope.

Furthermore, by moving the microscope's slide upon which particles are placed to focus the particles, they will move afterwards, implying yet another waste of time [31]. With automated technique, however, this operation is only required once, but once the image has indeed been acquired, we work in post-processing.

Last but not least, there is this significant benefit of this automated methodology in terms of time savings. Simply take a picture of the particles after they have been placed on a base with an appropriate background [34]. In a few seconds, a report with all of the information about the particles in the photo will be available.

CHAPTER 5

CONCLUSION

This project describes a method for counting and classifying microplastic particles into different morphological classifications that shows promising results. Computer Vision techniques are used in the procedure to count the particles present in the sample images.

Because of the use of computer vision techniques, it is possible to count and divide MPs into different types automatically and save a significant amount of time. Counting each particle in every sample becomes time consuming and hectic when there is large number of samples to be analyzed. Where-as when we use image processing techniques, quantification and counting of microplastic particles in different samples becomes simpler and quicker. The algorithms can be directly employed to different sample images and the results can be generated in a short span of time.

For greater accuracy of particle counts, it is very important to have good picture quality so that the distortions and noise are minimized. A sample image with less to no shadow cast gives more accurate particle count.

The morphology of microplastic particles detected in this paper are fragments, fibers and pellets. Fragments were the most common shape in the samples, with fibers coming in second. In comparison to fragments and fibers, pellets were quite few in count.

Microplastic pollution is becoming an issue of concern now considering the amount of plastic product being used in today's world. Plastic waste in the marine environment is alarming because it is constantly present in the natural environment and has detrimental effects on marine biota, and is transferred along the food web, which is a concern. At the international, national, and local levels, there is an urgent need to take tough steps to address the problem. Bigger plastic particles disintegrate into smaller pieces which get into our water system and pollute them.

Our approach has the potential to be used for a wide range of monitoring operations due to its ease of use and versatility, such as the detection and quantification of microplastic particles in different water systems using aerial images. This method will help in quality checking the water samples which are polluted by plastic.

Computer vision techniques can help speed up the quantification, characterization, and categorization of microplastic particles, and they can make a significant contribution to this growing subject about microplastic pollution.

It is impossible to compare different microplastic investigations because there is no worldwide regulated microplastic monitoring approach. It is critical to develop and apply a standardized strategy for collecting sample and reporting microplastic data. Because samples are easily contaminated during collection and laboratory work, future studies should focus on improving the blank control sample technique to reduce contamination. Moreover, samples should be taken in both the winter and summer seasons as seasonality has a significant impact on microplastic abundance and accumulation in water systems.

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