

Deep Learning Algorithm for Identifying Microplastics in Open Sewer Systems: A Systematic Review

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-----ABSTRACT-----

Microplastics (MPs) are small and tiny particles of plastics. They originate from macroplastics that have broken apart in the ocean. Plastic could also be broken apart due to weathering from the sun, wind, or other causes. The microbeads in many personal care products, such as toothpaste and facial scrubs also count as Microplastics. These Microplastics are destructive to marine habitats. MPs have been known to kill fish and other organisms that fish feed on. Blue economy management has attempted to control the spread of MPs in water bodies. This research was conducted to find out the work that has been done towards Deep Learning algorithms that identify features in pictorial images and which best Deep Learning algorithm can be used in identification of Microplastics. We used secondary data and a total of 1200 articles were reviewed, which, among these, ranged from medical science, environmental science and computer science. Only 23 articles proved relevant to our study. Our findings revealed that most techniques used in other fields cannot be employed in large scale detection, while in computing and IT, Deep Learning has been used, and that CNN is the best algorithm for feature extraction in pictorial images. We could not find any work that has fully employed one of the deep learning methods that used image photos taken from open sewer system to detect presence of Microplastics. We concluded that further research work could be done that will use photos with CNN's Deep Learning to identify Microplastics features in photographic images taken from open sewer systems.

KEYWORDS;- Microplastics, Blue Economy, Ecosystem, Machine Learning, Deep Learning, TensorFlow

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I. INTRODUCTION

Microplastics are small plastic particles less than 0.2 inches (5 millimeters) long, according to the National Oceanic and Atmospheric Administration (NOAA) (Nan, et al., 2020). In 2014 alone, researchers estimated there to be up to 51 trillion pieces of Microplastics in the ocean. This quantity outnumbers the stars in the Milky Way by 500 times (Hanvey, et al., 2017).

In contrast, macroplastics are larger objects like plastic bottles, hair combs, and toothbrushes. Both types of plastic continuously flow into the ocean, but Microplastics prove much more challenging to remove due to their small size. Volunteers can easily pick up large items during beach cleanups, but Microplastics are often too small to spot or grab in moving water (Shim, et al, 2017).

Researchers study Microplastics by using plankton nets, which have mesh netting that measures 0.004 to 0.02 inches (0.1 to 0.5 mm), small enough to capture plastic particles (Lindeque, et al. 2020). Others conduct visual surveys, though this method can be hard to use because of the variation in techniques.

How are Microplastics made? Microplastics often originate from macroplastics that have broken apart in the ocean. Plastic may break apart due to weathering from the sun, wind, or other causes. The microbeads in many personal care products, such as toothpaste and facial scrubs, also count as Microplastics. Microbeads often consist of polyethylene plastic, though they may also contain polystyrene or polypropylene.

Most of the methods used to analyzing presence of Microplastics debris, typically were, waterborne Microplastics samples taken using nets with a 333 μm mesh. This method of sampling, classifying and enumerating this inexhaustible pollutant in marine waters has proven challenging because smaller debris cannot be accounted (Lindeque, et al. 2020).

However, Sobhani, et al. (2020), used visualization technique to analyze Microplastics on the surface of the ocean. In their study, they demonstrated that Raman imaging can be employed to visualize and identify Microplastics and Nanoplastics down to 100 nm, by distinguishing the laser spot, the pixel size/image resolution, the Nanoplastics size/position (within a laser spot), the Raman signal intensity. The problem with this method is the collection of data for analysis. This will be improved by Machine Learning visualization technique, which this study proposes.

Deep learning is the ultimate of machine learning approach, which is concerned with utilizing Artificial Neural Networks (ANNs) to solve computer vision tasks such as image classification, object detection, and pose estimation. Pattern recognition applications have been one major success of deep learning which makes it relevant for this study. A number of algorithms of Artificial Neural Networks can extract features from various data formats such as text, images, videos etc. These algorithms are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and, Deep Neural Networks (DNN).

In Deep Learning, neural networks are layered, meaning, it refers to more than one layered neural network architectures. Each layer brings us closer to the desired result, and the more the layers, the more refined the result is. This is what the word “deep” means – going deeper and deeper into several layers for some accuracy in the result of data analysis.

Artificial Neural Networks which is used in Deep Learning, imitate the structure of inner working of the human brain in the way it processes data and implements decisions based on that data. The data is processed in a nonlinear approach because of the web-like structure of artificial neural networks. This makes Deep Learning more advantageous in analyzing data in form of images than other Machine Learning algorithms which are linear in nature.

In deep learning, a Convolutional Neural Network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Convolutional Neural Networks have a different architecture than regular Neural Networks. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. The output layer is a last fully-connected layer which represents the predictions.

This feature makes CNN relevant for Microplastics detection on images of pictures taken from open sewer systems. Chaczko, et al., (2020), tried the Neural Network algorithm trained with Hyperspectral images. However, since data about Hyperspectral Imaging of Microplastics was not used for the study, it could not be concluded as being effective. Again Hyperspectral Imaging is a very expensive technique because the cameras cost close to one million dollars. We propose to use normal cameras but with powerful picture resolution for our data collection.

II. Literature Review

Deep Learning

Deep Learning is the most advanced form of machine learning, involving the use of Artificial Neural Networks (ANNs) to address computer vision problems like picture categorization, object detection, and motion analysis (Chan et al., 2020). Pattern recognition applications have been one major success of Deep Learning (Moen et al., 2019), making it relevant for this study. Several Artificial Neural Networks methods can extract features from a variety of data forms, including text, photos, videos, and so on. These algorithms are Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN).

In Deep Learning, Deep Neural Networks are of several layers, referring to more than one layered neural network architecture. Each layer moves closer to the desired result, and the more layers, the more refined the result will be. From that perspective, we get the meaning of the word “deep” – going deeper and deeper into several layers for some accuracy for the result of data analysis.

Artificial Neural Networks which is used in Deep Learning, imitate the structure of inner working of the human brain in the way it processes data and implements decisions based on that data. The data is processed in a nonlinear approach because of the web-like structure of artificial neural networks. This makes Deep Learning more advantageous in analyzing data in form of images than other Machine Learning algorithms which are linear in architecture.

Convolutional Neural Network (CNN)

In Deep Learning, a Convolutional Neural Network (CNN or ConvNet) is a group of Deep Neural Networks most frequently used in analyzing visual imagery. Convolutional Neural Networks were inspired by how the human brain works - biological processes that show the connectivity pattern between neurons resembling the organization of the animal visual cortex (Chauhan et al., 2018). Convolutional Neural Networks have a different architecture than regular Neural Networks. In CNN, every layer is a set of nodes called neurons where each layer becomes fully connected to all neurons in the preceding layer. The predictions are the representation of the result layer, which is the last fully-connected layer.

CNN are sometimes applied elsewhere but were designed specifically for computer vision. Convolutional layers, which differ from conventional or thick stacks in canonical ANNs, are the source of the name Convolutional Neural Network. They were created with the purpose of receiving and processing pixel data, which is a key element to our study.

Convolutional Neural Network (CNN or ConvNet) is one of the AI techniques from Deep Learning that takes in input images, assigns significance, what are referred to as discoverable weights and biases, to various aspects of the image, and can differentiate one features from the other. Comparing other classification techniques and CNN, the initial preparation of data for modeling requirement in CNN is much lower.

The architecture of a ConvNet, which is comparable to the way network of Neurons are formed in the brain of a human being, was motivated by the positioning of the lens of human eyes called visual cortex. Each of the nodes (neurons) reacts solely to impulses in the Receptive Field, a limited portion of the field of vision. A group of homogeneous attributes can be piled on top of one another to fill the whole visual field.

An image is nothing more than a pixel value matrix. A Convolution layer could strongly render the dimensional and transitory associations in a picture by using appropriate filters. The CNN construction provides better fitting to the picture dataset because of the reduced number of variables required and the reusability of weights. This means that the network could be trained to discern the image's complexity.

CNN makes use of spatial correlations found in the input data. Some input neurons are connected by each concurrent layer of the neural network. A local receptive field is the name given to this area. Hidden neurons are the center of the local receptive field. The input data is processed by the hidden neuron inside the given field, with no awareness of changes outside the defined limit.

How CNN works

There are three layers in a Convolutional Neural Network. We can comprehend each layer individually with the help of an illustration of a classifier. It can be used to classify an X and O image. As a result, we will be able to comprehend all four layers with the help of the instance.

Convolutional Neural Networks are activated by volume and utilize multi-channeled picture. CNNs, on the other hand, cannot tell the difference between flat images with simply width and height, as perceived by humans. CNNs blend the three colors to generate the range of colors that people view since RGB encoding is utilized in digital color images.

A Convolutional network consumes such images as three distinct color strata stacked on top of each other. The width and height of a typical color image are defined by the amount of dots in those measurements. The depth levels of the three layers of RGB color that CNNs understand are called channels.

The Convolutional layer is the first layer of a CNN network and is the foundational structural piece that does the main work of the computation. Filters or kernels could be used to combine data or images. Filters or kernels are small units utilized to apply to data in a sliding window. The depth of the image is the same as the input; for instance, if the RGB value of depth for a color image is 20, a filter with a depth of 20 is used. For each sliding movement, this method involves taking the element-wise product of filters of the image and adding those specific values. A convolution with a 3d color filter would yield a 2d matrix.

Convolutional Neural Networks have the following layers:

1. Convolutional
2. ReLU Layer
3. Pooling
4. Fully Connected Layer

A number of steps are involved in this process. It is important that the dataset is first downloaded and the function to encode the labels is run. This would be followed by picture resizing to 50 by 50 pixel and converted to grayscale. The data is then split in a ration of 80:20 for training and testing in that order. The data is reshaped appropriate for TensorFlow after which a model is built and a loss function is then calculated. The following diagram would show the process:

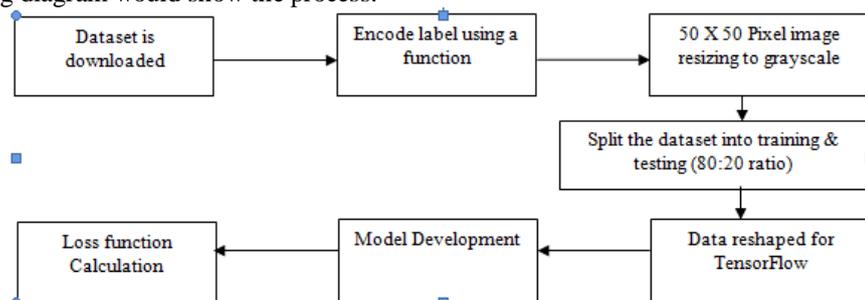


Fig. 1 Convolutional Neural Networks process

Recurrent Neural Network (RNN)

The nodes of a Recurrent Neural Network (RNN) are linked in a directed graph that follows a linear association. Recurrent Neural Networks (RNNs) are feedforward neural networks that use their internal state to process input sequences of any length (memory). Recurrent neural networks (RNNs) are a form of neural network that can model sequence complex data. RNNs which are formed from feedforward networks, are similar to human brains in their behavior. In a manner that other algorithms cannot, they can anticipate sequential data (Banerjee et al., 2019).

RNNs have a unique architecture that allows them to model memory units (hidden state) and so model short-term dependency. RNNs are widely employed in time-series forecasting to find data correlations and patterns because of this.

The "time series version" of Artificial Neural Networks is the Recurrent Neural Networks (RNN). The RNN are designed to deal with data successions. They serve as the foundation for forecasting and linguistic models. LSTM (Long Short Term Memory) and GRU (Gated Recurrent Units) are the most common types of recurrent layers; their cells contain small, in-scale ANNs that determine how much previous input should flow through the network. They modeled "memory" in this way.

Deep Neural Network (DNN)

A Deep Neural Network (DNN) is an artificial neural network (ANN) that forms other hidden layers between the input and output layers. Neurons, synapses, weights, biases, and functions are all components of neural networks, which come in a variety of shapes and sizes.

A deep neural network (DNN), sometimes known as a deep net is a neural network with some amount of complexity, often at least two layers. Deep neural networks use advanced mathematics modeling to process data in complex ways.

Pollutants

There are so many types of pollutants, ranging from chemicals to microorganisms. These pollutants find their way into water bodies, especially the sewer, which is the main carrier of these materials to other water bodies such as the rivers, lakes and oceans. The streams that flow from the backyards, industries, and homes carry these materials of which some are readily found on the sand. Plastics are the major concern for this study, especially the Microplastics. This is because pollution that stems from plastic has evolved into one of the most arising issues threatening marine life and earthbound ecosystems, (Zhu et al., 2020). Plastics are divided into macroplastics and Microplastics.

Macroplastics

Macroplastics are bigger articles like plastic jugs, hair brushes, and toothbrushes. These objects continuously flow into the ocean. However, they do not prove much of a challenge to removal due to their big size. These objects are easy to pick up during beach cleanups, though they pose dangers of degenerating to Microplastics and carriers of other germs and bacteria that are harmful to the living things in water, such as fish, (Shim, et al., 2017).

Microplastics

Minuscule plastic particles that measures not more than 0.20 inches or 5 millimeters in length are known as Microplastics, according to the National Oceanic and Atmospheric Administration (NOAA) (Nan, et al., 2020). These are tiny pieces of broken larger plastics that cannot easily be seen by naked eyes. Researchers found that there were more than 50 trillion pieces of Microplastic in the ocean in the year 2014. This number is estimated to be 500 times greater than the number of stars in the galaxy (Hanvey et al., 2017).

Microplastics are pollutants that can get into human body through the food chain and for that matter, they pose a serious threat for biological organisms and to the environment (Cheng et al., 2021; Dey et al., 2021; Kumar et al., 2021).

Microplastics absorb toxic metals, microorganisms, and other chemical additives used in plastic material manufacture, making them a possible vector for diseases. People ingest these Microplastics from the food consumed such as Fish, and other edible aquatic creatures. Over a period of time, these ingested Microplastics block digestive tracts, hence interfering with digestive behavior which result in decreased reproductive growth of human beings and other living organisms that ingest them (Dey, et al, 2021). Marine ecosystems report the highest presence of Microplastics. However, freshwater ecosystems, such as in lakes, ponds, river basins, wetlands, or even in moist agricultural lands and groundwater, also report a magnitude presence of Microplastics, (Kumar et al., 2021). Kumar et al., (2021), in their conclusion of their study, found out that the common polymeric types of Microplastics in wetlands are polyethylene, polypropylene, and

polystyrene. It is also very important to note that Microplastics decomposed by solar UV radiation and waves can accumulate in the human body, (Jeo, et al., 2020).

Techniques used to detect Microplastics

According to Dey et al. (2021), there are two methods for detecting Microplastics: physical and chemical. They say that stereomicroscopic detection is better for large particles that can be enlarged by staining prior to microscope visibility, but that spectroscopic approaches are also generally accepted analytical techniques for this objective. Microplastics are detected using FTIR, a chemical non-destructive approach. According to them, plastic particles are exposed to infrared light in this approach, and an adequate spectrum for the vibration of a chemical connection between various atoms is established. FPA-FTIR, TGA-FTIR, and Raman could improve this approach. Researchers are exploring employing remote sensing as a preliminary screening method for Microplastics, they concluded.

PZhu et al., (2020), used Hyperspectral imaging in detecting Microplastics by optimizing a commercially available Hyperspectral imaging system. They used Pika NIR-640, a product manufactured by Resonon Inc. from USA. They found out that the detection resolution of each pixel improved from 250 μm to 14.8 μm after optimization, which they could now rapidly detect down to 100 μm in size of Microplastics particles.

Chen et al. (2021) aimed to create a simple and effective classifier for identifying the environmental Microplastics category. They suggested a robust classifier to adjust an adaptive distance estimation in traditional k-NN and avoid the detrimental impact of spectral distortions induced by environmental contaminants or plastic degradation, utilizing four types of MPs and over 400 spectra to demonstrate the model's performance. Their findings revealed that the new method outperformed the traditional k-NN, with average identification accuracy increasing from 0.919 (by k-NN) to 0.975 (by proposed method) (by robust k-NN). They came to the conclusion that spectral technology combined with a robust k-NN classifier method can successfully identify environmental MPs.

Chaczko, et al., (2020) used Hyperspectral images to see if they could be used successfully in Neural Networks, with the goal of using Hyperspectral images in Microplastics pollution studies. They employed a dataset of spectral pictures of sixty textile samples with various texture patterns. They concluded that their evaluation of a thousand iterations of training data had a correct classification of 95 out of 100. They could not comprehensively conclude about the results because they did not have data about Hyperspectral imaging of Microplastics at the time of the study in the public domain. They were however, confident that their research showed that a Neural Networks model trained using Hyperspectral pictures of Microplastics could be useful.

Linda Schedl, (2020), in her research of Microplastics detection using Machine Learning algorithms, found out that Microplastics can be characterized by Fourier-Transform Infrared (FTIR) spectra. She also noted that these (FTIR) spectra can be classified with the aid of supervised learning algorithm, and compared a number of these algorithms, k Nearest Neighbor (k-NN), Support Vector Machine (SVM) and Random Decision Forest (RDF), and concluded that SVM exhibits long training time while k-NN exhibited long prediction time. According to her training time was not a big issue, but prediction time was, especially for large data set. These disqualified k-NN. She also noted that SVM and k-NN tend to assign single pixels to classes that were not present, while RDF never assigned any. But she concluded by saying the issues with SVM and k-NN can be resolved by applying post processing to the output of the binary classifiers rather than just assigning the most probable class.

Presumption

After reviewing and examining most of the documents, we can say with high certainty that Microplastics exists in large numbers and poses a great threat to the environment and the ecosystem, starting from the living organisms in the water bodies such as the ocean, lakes, rivers, etc. This pollutant, MPs, must be addressed, as we have seen above, most researchers have used both physical and chemical techniques in trying to detect the presence of Microplastics, especially on the ocean.

These techniques some of which are good, but have a limitation of time and work involved in analyzing data to detect the presence of Microplastics on the ocean. Some require the use of lab after a hectic exercise of collecting particles of MPs on water using sieves or nets of different sizes. Linda Schedl, (2020), was closer to using a friendlier and modern technique by employing the use of supervised machine learning techniques, by comparing three algorithms to find which one, or which combination would give the best optimal result. Chaczko, et al., (2020), tried the Neural Network algorithm trained with Hyperspectral images, which is also machine learning technique. However, since data about Hyperspectral imaging of Microplastics was not used for the study, it could not be concluded as being effective. Again Hyperspectral Imaging is a very expensive technique because the cameras cost close to one million dollars.

From the perspective of Chaczko above, we are seeing a gap given the fact that Hyperspectral Imaging is very expensive; a cheaper technique would be more desirable. This work proposes a different approach to detection of Microplastics, especially on the open sewer systems and the manner in which data is collected and processed. The proposed method will be able to address the drawbacks of most of the methods so far been used, such as time for collection of data, work involved in detection and the cost for doing that exercise.

III. Conceptual/Theoretical Framework

Deep Learning has becoming a tool for Multidisciplinary level. Study of Microplastics involves concerted efforts from a multidisciplinary level, where each discipline is struggling to propose a better solution or indicate an avenue for further work that could lead to creating a solution. In that regard, we have directed our focus on the direct disciplines that might have attempted at handling this problem. This is shown by the diagram below with the following variables:

Ecosystem, Ecology, Environmental Science, Medical Science, Geography, Public Health Science, Computer Science, and Information Technology.

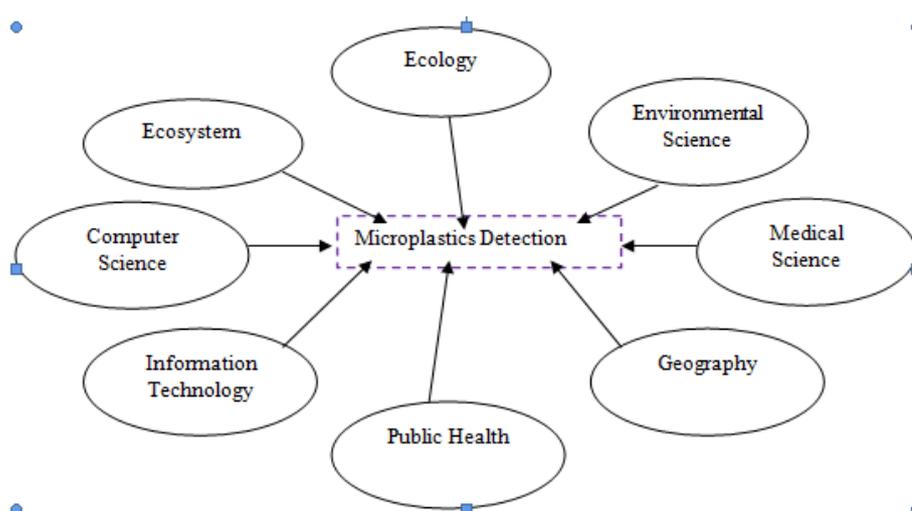


Fig. 2 Conceptual Framework

In Computer Science and Information Technology, we were keen on review work that was focused on Artificial Intelligence, especially Machine Learning with more specific to Deep Learning. As we reviewed articles in other disciplines, our focus was on what methods were employed and what solutions were found and if not, what can be borrowed in formulating a solution using a differing techniques from Computing discipline. In computing and IT, our focus was on the Deep Learning algorithms that work best with the data set for Microplastics identification.

Research question

What deep learning techniques exist that are used for image processing and how can these techniques be used to identify Microplastics (MPs) in open sewer systems?

Materials and Methods

Majority of work from the literature reviewed had no specific organization or trend that one could pick from. We were forced to create that trend based on the framework outlined above. The material was searched randomly from various databases and from the Internet in general. The framework provided the guide because we had to look at each category of the interdisciplinary levels to find out what contributions came from each as well as the number of efforts made. We needed to understand; first, about Microplastics; second, their effects to the ecosystem; third, their detection.

Using the frame work as our base, the need to understand formed our study design. Being random search method, we were satisfied by materials got from each discipline and thus did not tabulate the number of efforts made in each category. We adopted the above strategy because we were convinced that the above will answer our research questions.

IV. Results and Discussions

Our study revealed that Convolution Neural Network in Deep Learning is an effective algorithm that can be used to identify features in a pictorial image. It showed that the same algorithm can be used to identify features of Microplastics from photographic images taken from open sewer systems. Again, after reviewing and examining most of the documents, we concluded that Microplastics exists in large numbers and poses a great threat to the environment and the ecosystem, starting from the living organisms in the water bodies such as the ocean, lakes, rivers, etc. This pollutant, MPs, must be addressed, and as we have noted the articles, most researchers have used both physical and chemical techniques in trying to identify Microplastics, especially on the ocean.

Many research adopting Artificial Intelligence tried a mix of IFTR and Machine Learning which did not give much of a result. However, few tried with Hyperspectral Imaging using other materials, other than Microplastics, which again, was far from proving a tangible solution to the identification of Microplastics in open sewer systems before flowing to the ocean or other water bodies.

It is known that disciplines borrow from each other and help each other in finding solutions to societal problems. More so, IT is disciplines that provides or enable other disciplines solve problems. Environmentalists are looking for solutions on how to deal with Microplastics as a pollution menace. A lot of research has been done regarding the same. A number of solutions have been seen, however implementation of some of the models are prohibitively expensive. Few researchers in IT have tried the same but somehow used some of the science lab techniques in conjunction with AI, especially Machine Learning algorithms such Naïve Bayes, k-Nearest Neighbor and so on. The models are still expensive to implement. Further research is need to see how pictures can be used together with Deep learning to detect the presence of Microplastics in open sewer systems.

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