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Rapid detection of microfibres in environmental samples using open-source visual recognition models

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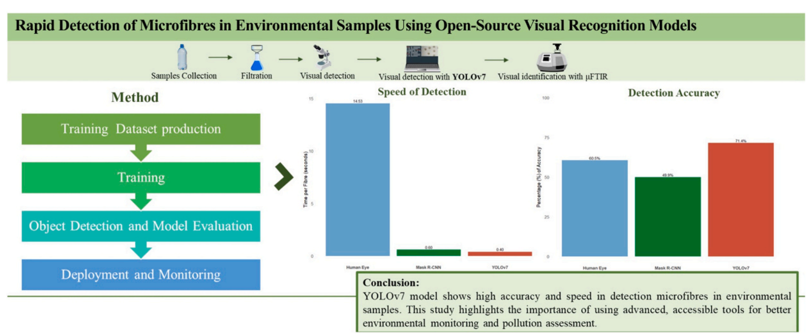
HIGHLIGHTS

- The study uses YOLOv7 and mask R-CNN to detect microplastic fibres.
- Accuracies were 71.4 % (YOLOv7) and 49.9 % (mask R-CNN) for environmental samples.
- Both offer rapid quantification of microfibres (0.4-0.6 fibres per second).
- Both models are open source, and usable with limited knowledge of coding.
- Speed and accuracy highlight use in environmental microplastic fibre detection.

GRAPHICAL ABSTRACT



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ABSTRACT

Microplastics, particularly microfibres (< 5 mm), are a significant environmental pollutant. Detecting and quantifying them in complex matrices is challenging and time-consuming. This study presents two open-source visual recognition models, YOLOv7 and Mask R-CNN, trained on extensive datasets for efficient microfibre identification in environmental samples. The YOLOv7 model is a new introduction to the microplastic quantification research, while Mask R-CNN has been previously used in similar studies. YOLOv7, with 71.4 % accuracy, and Mask R-CNN, with 49.9 % accuracy, demonstrate effective detection capabilities. Tested on aquatic samples from Seyðisfjörður, Iceland, YOLOv7 rapidly identifies microfibres, outperforming manual methods in speed. These models are user-friendly and widely accessible, making them valuable tools for microplastic contamination assessment. Their rapid processing offers results in seconds, enhancing research efficiency in microplastic pollution studies. By providing these models openly, we aim to support and advance microplastic quantification research. The integration of these advanced technologies with environmental science represents a significant step forward in addressing the global issue of microplastic pollution and its ecological and health impacts.

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1. Introduction

Plastics are ubiquitous in everyday life due to their widespread manufacture; from 1950 to 2020 their worldwide production increased from 1.5 to 367 million tonnes per year [1,2]. There is now a global consensus that their production and subsequent inappropriate disposal are a source of severe contamination of the environment [3,4]. Plastics degrade very slowly [5] and the length of time they remain in the environment remains unknown. Around 79 % of plastic waste has been discarded in landfills or directly in the environment [6] due to poor waste management and natural processes. Researchers have demonstrated that up to 90 % of marine litter found in different marine bodies is plastic [7]. Due to their persistence in the environment, many plastics degrade into smaller shapes and sizes, which are classified as macroplastics, mesoplastics, microplastics and nanoplastics.

Microplastics have generated huge interest from research, media and the public [8]. No official size definition has been universally agreed for microplastics, even though it is commonly held that they are defined as plastic particles < 5 mm [9-16]. The first evidence of microplastics in the environment was recorded by Carpenter and Smith [17], who recovered an average of 3500 plastic particles equating to an abundance of 290 g/km^2 from surface water in the western Sargasso Sea [17]. Microplastic particles, primarily consisting of fibres, find their way into our ecosystem through multiple pathways, including the discharge of domestic and industrial wastewater, runoff from landfills, and even deposition from the atmosphere [18]. Since the early 1970s when plastic particles were first acknowledged to exist in the aquatic environment, there has been a growing body of evidence documenting the ingestion of microplastics by animals, particularly seabirds. Over time, an increasing number of reports have highlighted this phenomenon [19-21].

Many studies have investigated microplastic abundance in the environment. In the majority of these surveys, the quantification of microplastics (MPs) is conducted using the traditional technique of plastic particle counting under an optical microscope. This method is labour intensive and prone to human error, and research has demonstrated that human bias can have an impact on the measurement of microplastics [22,23]. For example, blue fragments have the highest detection rate, while white fragments have the lowest [24]. In addition, preparation, extraction, and identification procedures vary across samples from different water bodies and/or sediments, as they do not adhere to a uniform protocol. For example, processing samples from bottled water [25] is simpler than samples from beach sediments [26] due to the absence of complex particulate matter, organic debris, and variable mineral compositions present in sediments. This variability in sample complexity can lead to inconsistencies in analytical results, potentially impacting the accuracy and comparability of microplastic quantification across different environments.

Analysing environmental samples from various sources, such as saltmarshes, soil, or water bodies like rivers, lakes, and oceans, is indeed challenging for several reasons. One significant challenge lies in the preparation process of these samples. The collection, handling, and processing of environmental samples often requires specialized equipment and trained personnel, making it time-consuming and expensive [27]. The preparation process involves sample collection, transportation, storage, and extraction of target analytes (substances of interest, microplastics) from the samples. Each of these steps can introduce potential errors, contaminations, or losses of the target analytes, leading to inaccuracies in analysis. Moreover, the diverse and dynamic nature of environmental samples can make it difficult to standardize the preparation process, further adding to the complexity and potential variability of results [28,29].

In the last decade, there has been an increasing interest in using computer vision techniques in the microplastics field [30-32]. Deep learning models and automated image techniques have been implemented to detect, quantify, and classify microplastics [33-37,32]. Numerous deep neural networks have been developed, such as ResNet (Residual Neural Network) [38], U-Net (U-shaped encoder-decoder Neural Network) [39] or R-CNN (Region-based Convolutional Neural Network) [40]. Previously, studies have described an effort to apply deep learning-based object detection methods to identify plastic marine litter using autonomous underwater vehicles and remotely operated vehicles [41-43]. The automation of these measurements not only increases efficiency but also potentially reduces the likelihood of human error.

Building on these advancements, the field has adopted a more sophisticated application of these methodologies. Specifically, the integration of deep learning imaging techniques and analytical tools has refined the analysis of microplastics by focusing on key attributes such as size, shape, and colour of microplastics, enabling researchers to differentiate these particles from other materials in environmental samples. The table below provides a concise summary of these techniques, highlighting their accuracy, user-friendliness, and whether explicit coding knowledge is required (Table 1).

Through the development of various models, as detailed in the accompanying table (see Table 1), a clear common limitation emerges; the absence of an open-source machine learning model capable of directly analysing environmental samples without the prerequisite of pre-treatment.

This a significant limitation, considering the diverse environments from which samples are collected, and the varying requirements for sample pre-treatment. For instance, while the MATLAB Algorithm and SMACC require pre-treatment for beach sediment analysis, U-Net and VGG16, as well as Holographic Imaging, do not necessitate such preparation for laboratory samples. However, the accessibility of these technologies is constrained; models like the MATLAB Algorithm are not publicly available without licence, and others, such as DCNN and Mask R-CNN, require specific requests for access.

However, despite their high accuracies and advanced capabilities, many of these models remain inaccessible to a significant portion of potential users. Addressing this challenge necessitates identifying methods that eliminate the need for pretreatment, offer free access, and require minimal specialised knowledge. Although certain techniques fulfil the pretreatment criterion, they remain limited by issues of accessibility, complexity, and cost. Consequently, open-source solutions emerge as the optimal response, underscoring a clear distinction between open-source and proprietary models in terms of accessibility and ease of use. Open-source tools like YOLOv7 ("You Only Look Once" version 7) are free and user-friendly, and only require a low level of coding knowledge, offering a balance that makes them suitable for a broader audience. In contrast, proprietary tools, although potentially offering advanced features, often come with higher costs and a steeper learning curve.

Thus, the YOLOv7 model, despite the high accuracy achieved by existing models, such as ResNet, U-Net, and R-CNN. While these models are highly accurate, they often require specialised expertise and substantial computational resources, which can limit their broader application. YOLOv7 addresses these limitations by offering a more accessible and resource-efficient alternative that can be deployed on conventional GPUs.

In addition, existing models are typically trained on controlled datasets, which may not fully capture the complexity and variability of real-world environmental samples. YOLOv7, in contrast, has been tested on diverse environmental samples, demonstrating its robustness in detecting microplastic fibres under challenging conditions. The model is specifically designed to handle the varied shapes and interactions of microplastic fibres, making it particularly effective for this purpose.

Finally, the open-access nature of YOLOv7 promotes transparency and collaboration within the scientific community, allowing continuous improvement and adaptation of the model to meet evolving research needs. The manuscript has been updated to highlight these advantages and to explain the broader benefits of using YOLOv7 in this study.

In light of these considerations, this research investigates YOLOv7 and Mask R-CNN models for the detection of microplastic fibres. These models stand out in their ability to handle the diversity of microplastic forms and shapes, particularly in challenging environments. This approach addresses the limitations of both open-source and proprietary models by offering an optimal balance of accessibility, accuracy, and ease of use.

Microplastic fibres are an underestimated threat to the environment [50] and humans [51], and present a high risk of contamination during sampling and analysis [52,53]. Analysis of images taken by a microscope is a tedious task, as it requires a lot of time to detect and focus, and the photos are not always perfect; they may need further image processing. In addition, different microscopes, lighting conditions, magnifications, quantity of samples can make the work even harder for the human eye. Hence, the automation of image-based identification emerges as a promising solution for particle counting and classification. However, this endeavour is not without its challenges, owing to the variability in architectural designs, algorithms, and training methodologies. The success of any neural network hinges upon the availability of a well-curated training dataset, tailored to address the intricacies of real-world classification and identification challenges [54].

This study focuses on utilising computer vision to automatically detect the presence of microplastic fibre in images, employing two supervised learning models: YOLOv7 and Mask R-CNN. These models were specifically trained for the detection of fibres, which are the most abundant and challenging type of microplastic in the environment [55]. The complexity in detecting these fibres arises from the diverse forms and shapes, and their tendency to become entangled or attracted to other particles.

YOLOv7 is an algorithm that detects and recognises various objects in a picture. YOLO is built on the concept of achieving the best possible combination of speed, accuracy, and parallel computation, and the method is one of the most widely used deep learning-based object detection techniques. YOLO is used across many commercial fields, such as face detection [56], traffic detection [57] and tiger detection [58]. The goal of object detection is to detect objects in an image or a video and classify them. In the last few decades, deep learning algorithms have achieved improved performance in terms of robustness, accuracy, and speed for multi-classification tasks [59,60]. YOLOv7 stands out due to the optimised architecture, allowing for faster processing of images and videos, making it particularly suitable for real-time applications. Although newer versions, such as YOLOv8 and YOLOv9, are now available, YOLOv7 was selected for this study because its proven reliability and robustness at the time of the research. Notably, YOLOv8 was developed by different team (Ultralytics) than the initial YOLO model lineage, with no official documentation. While YOLOv9 developed by the same team as YOLOv7, is a very recent release (February 2024) [61].

Mask R-CNN (Regional Convolutional Neural Network) will be examined as the second potential candidate model to quantify microplastics. A model that already have been used for microplastic quantification [48,49]. CNN (Convolutional Neural Network) models offer improved accuracy, efficiency and flexibility in the processing of images, videos and audios [37]. The Mask R-CNN creates a binary mask around the detected object separating it from its background. This pixel-level instance segmentation model has been applied in various projects; including medicine [62,63], agriculture [64], and engineering [65] (Fig. 1).

YOLOv7 and Mask R-CNN were selected because they are freely available to anyone who uses a conventional GPU (Graphics Processing Unit), to train and test images. Advanced accessible models allow a broader range of researchers and practitioners, including those with limited resources, to contribute to and benefit from the advancements in the field [66,67]. In both cases, a training dataset requires the human operator to label the features (fibres) in the data, which is then used to train the computer vision algorithm. The algorithms offer the advantage of speed and high accuracy with minimal background errors. In addition, they have excellent learning capabilities, enabling them to learn

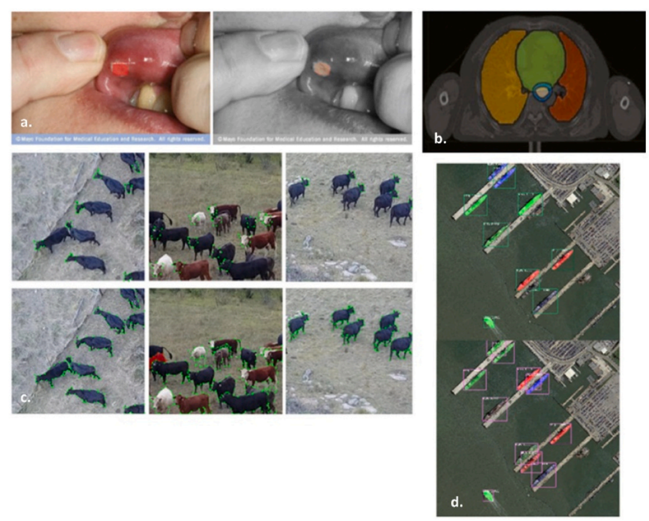

Fig. 1. Mask R-CNN used in various projects: a. Detection of oral diseases [62], b. Detection of multiple organs [63], c. Detection for monitoring cattle [64], d. Inshore Detection Mask R-CNN and author's model [65].

Table 1
Comparative Summary of Microplastic Detection Methodologies using photographic data collection: This table presents a quick comparison of techniques for identifying microplastics, emphasising key aspects such as accuracy, ease of use, technical requirements, and access.

Model/ Technique Used	Accuracy	Sampling Environment	Pre- Treatment required?	Open-Source?	Authors
Automated Microplastic Detection and Characterisation Algorithm in MATLAB (Matrix Laboratory)	66.63 %	Beach sediment	Yes	License required	Gauci et al. Gauci et al., [44]
U-Net and VGG16 (Visual Geometry Group 16)	98.82 %, 98.11 %	Laboratory (manufactured microplastics)	No	No	Lorenzo-Navarro et al. Lorenzo-Navarro et al., [35]
SMACC (System for Microplastics Automatic Counting and Classification)	91.1 %	Beach sediment	Yes	Yes	Lorenzo-Navarro et al. Lorenzo-Navarro et al., [45]
MP-VAT (Microplastics Visual Analysis Tool)	Not specified	Laboratory (manufactured microplastics)	Yes	Open-Source	Prata et al. Prata et al., [46]
Holographic Imaging	99 %	Laboratory (manufactured microplastics)	No	Open-source dataset	Bianco et al. Bianco et al.,[47]
DCNN (Deep Convolutional Neural Networks) and Mask R-CNN	Not specified	Beach sediments, water, animal tissue and meta-analysis of published data	No	On request	Huang et al. Huang et al., [48] Sundar et al. Sundar[48, 49]

the representations of objects and apply them in object detection. Thus, YOLOv7 and Mask R-CNN are proposed as a simple and free-of-charge method. This new approach will be applied to real-world environmental samples.

The study intends to compare the effectiveness of YOLOv7 (a new use of the model for microplastic quantification) against Mask-RCNN (a model previously used for microplastic quantification). The YOLOv7 model is primarily focused on speed and efficiency, offering rapid detection of microplastic fibres with accuracy, making it particularly suitable for large scale environmental monitoring where quick results are essential. Its design emphasises accessibility and ease of use, allowing it to be implemented on conventional GPUs without requiring extensive computational resources. On the other hand, the Mask R-CNN model is designed for detailed segmentation, providing pixel-level accuracy in distinguishing microplastic fibres from other materials in complex environmental samples.

YOLOv7, known for its high speed and accuracy in object detection tasks, and Mask R-CNN, renowned for its pixel level instance segmentation and an already utilised microplastic visual recognition machine model, have been evaluated to determine their relative performance in detecting microplastic fibres. Through this comparison, the strengths and limitations of each model have been highlighted, providing valuable insights. The goal is to establish a robust and user-friendly methodology for rapid and accurate detection of microplastic fibres.

Thus, this work aims to apply a state-of-art method for automating the detection of microplastic particles using non-specific and/ or expensive laboratory equipment and minimally treated samples. This open-source machine learning approach has significant potential benefits over visual methods of microplastic identification by reducing human error which is known to be significant [68]. It also offers some practical advantages over other machine learning approaches which require a greater amount of pre-analysis such as addition of dyes [46], or application of complex microscopy techniques [69].

This study will provide an:

- Evaluation of YOLOv7 and Mask R-CNN algorithms on a unique dataset of varying- quality microplastic images to enable cost-effective, accessible pollution monitoring without the need for high-end laboratory equipment. The automated quantification of MPs particles by implementing object detection algorithms to evaluate environmental samples.
- Application of the trained YOLOv7 model to analyse environmental water samples from Iceland for microplastic pollution assessment.
- Comparison of the effectiveness of YOLOv7 (new to microplastic quantification) against Mask R-CNN (used before for microplastic quantification) on environmental samples.
- Introduction of user-friendly and cost-effective models for the detection of microplastics.

2. Materials and methods

i. Dataset production: Collect images or videos of microplastics in coastal area, particularly focusing on the regions where microplastics are likely to accumulate, such as shorelines, tidal zones, or areas near human activities. It's essential to note that the samples were pre-treated before image capture, ensuring an accurate representation of the microplastic presence in the environment. The images undergo a common pre-processing regimen, including resizing, noise reduction, and contrast enhancement. Further details on the methodologies and techniques used for sample pre-treatment and image pre-processing are comprehensively in Section 2.1.1 of the study.

ii. Annotation and Training: Annotate the images to provide the ground truth information about the location and size of microplastics in the training dataset. This annotated dataset is then used to train the object detection model to identify microplastics accurately. The detailed methodologies and techniques employed for the annotation process are thoroughly discussed in Section 2.1.4. Subsequently, Section 2.2 delves into how this training enables the model to effectively detect microplastic fibres.

iii. Object Detection and Model Evaluation: Use object detection algorithms to identify potential microplastics within the images. Deep learning-based object detection models, such as YOLO or Mask R-CNN, can be trained to recognize and localize microplastics. This evaluation, detailed in Section 4, involves using specific metrics to ensure it can reliably detect microplastics under various conditions.

iv. Deployment and Monitoring: In a practical application, the models, refined through a case study in Seyðisfjörður, are deployed to process and analyse new images or videos (testing dataset) collected from this coastal region. Regularly monitor the system's performance and fine-tune the model as needed to improve its accuracy. The ongoing process of monitoring the system's performance and fine-tuning the model to enhance its accuracy is crucial. This continuous improvement and adaptation strategy, which is essential for maintaining the efficacy of the models in dynamic environmental conditions, is further elaborated in Section 3.2.

2.1. Training and validation dataset production

The machine learning models selected for this study (YOLOv7 and Mask R-CNN require the preparation or specific training and test data sets to aid in the training and evaluation of the models. Human operators can quantify microplastics in different states (flat, round, long) and under various conditions using optical microscopes. If one of these parameters, like lighting or shape, is changed, then the human eye may miss the microplastic particles. So, visual recognition techniques try to imitate the human operator, but delivering results in shorter time and with less errors. Therefore, it is important that the training dataset images capture all potential states and characteristics of fibres to train the model. A large amount of diverse data, which reflect real-world conditions, is necessary to lead to accurate results. The validation or test dataset is a dataset on which the model has not been trained but has been produced to evaluate the accuracy of the model on 'real world' deployment.

2.1.1. Sample preparation

For the training and validation datasets, rather than seed samples with microplastics to produce images, images from a variety of filtered bottled water as well as environmental samples (n.= 15) were used. Bottled spring water was chosen as it presented a known source of microplastics in clean, natural, untreated water. No brands were focussed on, with availability and cost largely driving choice. The use of bottled water allowed the efficient generation of images for training without the need to produce seeded sample. The bottled water samples were filtered into a glass beaker and through a GF/F (Glass fibre F grade) filter (nominal pore size 0.7 μm; 47 mm diameter). The environmental samples in the datasets consisted of water samples collected from different environmental locations (e.g. rivers, estuaries and the ocean) Due to the presence of biological material in environmental samples they were treated in a different way from the bottled samples. The fjord water was filtered into a glass beaker and particles were concentrated on GF/F filter (nominal pore size 0.7 μm; 47 mm diameter). 25 mL of 30 % hydrogen peroxide was added to the filter paper, which was left at room temperature for 24 h. Following this, the sample was placed in a non-fan oven at 40 °C covered with foil [70,71]. The samples from bottled water did not undergo any hydrogen peroxide pre-treatment process.

Sample contamination from the laboratory is a constant challenge in microplastic research. To mitigate sample contamination, the lab procedures were carried out under a flow hood. Glassware was washed with

Decon 90 and muffled at 400 °C for 4 h before each use. All the equipment was rinsed with 3x filtered purified deionised water. Samples and equipment were covered with foil during the procedures to minimise exposure as much as possible. Filter blanks were placed parallel to the experiments to verify any air fall contamination. Particles detected on the filter blanks were analysed and compared to the filters from the environmental samples to assess laboratory contamination levels.

Microfibre detection was carried out visually and inspected with an an inverted microscope Nikon SMZ1270 (objective: Nikon Plan Apo 0.75x) microscope. The microfibres were characterised based on their colour (transparent, black, brown, red, pink/purple, blue, green, yellow, and orange) and based on the roughness of their surfaces [72-74]. To make sure identification of the MP fibres was correct, identified fibres were analysed using micro Fourier-transform infrared spectroscopy (μFTIR), performed using a Thermo Fisher Scientific Nicolet iN10 Infrared Microscope. The cooled detector was set up at an aperture of 25 × 25 μm, and the sampling mode employed was reflection. Using this technique, particles were classified as microplastics or natural which provided the basis for the generation of the images required for the training and validation datasets.

2.1.2. Training dataset image collection

The training dataset is a crucial role in the accuracy and the performance of deep learning models. In the context of detecting microplastic fibres in environmental matrices, the number of images per class can significantly impact and classify these objects accurately. However, the exact number of images required for an accurate detection remains elusive and varies across studies and models [75,76]. Research into image sample size for a wildlife based training dataset demonstrated that after 150 images per class the improvement in model's performance was negligible, with incremental improvement after 500 images [77]. Therefore, for the specific study, it was considered that, a dataset of 200 images with varying fibre positions and orientations against a white and/or brown background are sufficient to achieve reasonable classification accuracy. To train the model, 80 % of these images were used, while 15 % were reserved for unbiased validation, and the remaining 5 % for final model evaluation. This dataset, enriched with annotated and labelled images, serves as the foundation for the model to learn and recognise microplastic fibres. A model trained well on a diverse dataset with different fibre positions and orientations holds the potential to outperform its initial training environment and demonstrate its utility across a spectrum of environmental settings. To further ensure the robustness of the YOLOv7, the training dataset also included a variety of water samples, ranged from with no microplastics to others with densely packed microplastics. The model ability will be explored later during model testing on environmental samples from Iceland. It becomes versatile across various environmental matrices, enabling a diverse range of users, researchers and practitioners, to leverage the model's capabilities effectively.

To capture all potential states and characteristics of fibres within the samples and to train the models adequately, several methods of image collection were employed. 100 images from bottled and Icelandic water samples were taken with an inverted microscope Nikon SMZ1270 (objective: Nikon Plan Apo 0.75x) equipped with a 16.25-megapixel Nikon DS-Ri2 camera and 20 images with an iPhone XR 7-megapixel camera over a microscope. As an additional step to test the method's performance with alternate microscope types of images of 100 filters from environmental samples from Iceland were captured with a TOMLOV DM9 (12 megapixel) microscope. 50 were taken against a white background, and 50 against a brown background, in order to evaluate the effect of background colours on image recognition., Together, this approach reinforced the validity of the dataset across multiple sample types, with multiple image collection methods, similar to what might be expected during model deployments.

2.1.3. Image pre-processing

Size, orientation, light levels, and general image quality can affect identification of microplastic fibres. It was therefore considered essential to conduct multiple experiments to train the model to possible image invariances. Therefore, 30 % of images were further processed to capture fibres in different angles and colours, such as grayscale, smooth deformation, denoising, mirroring, saturation, and exposure. The images were pre-processed via Python programming as follows:

- Image rotation (90°, 180°, 270°) on 15 % of the images
- Image resizing in some images with dimensions (1366 ×768 pixels to 608 ×403 pixels)
- Gaussian blurring on the 5 % of the images
- Gray scaling on the 10 % of the images

These transformations are considered essential to avoid overfitting and improve the robustness of the predictive model. To perform these transformations, a script was created, which can edit batches of images automatically.

2.1.4. Annotation

YOLOv7 has been trained using image annotation to evaluate fibre detection. The image annotation tool is used to create boxes around the desired object and give it a label. Image annotation is a vital part of the model, as the model uses these annotations and labels to detect the same type of object in an unknown dataset. For this task, all the photos were labelled using LabelImg (Windows_v1.8.0) by tzutalin (GitHub). LabelImg is a graphical image annotation tool, where the labeller draws a box around the object. The annotations are saved as XML (Extensible Markup Language) files in Pascal or YOLO format. The model is trained based on these boxes. At this stage, it is important that the resolution of the images is high enough to maintain the details of small objects, so they are not blurry when downsized during the training.

The training dataset for R-CNN has been carried out using image segmentation through the freely available photo-labelling tool, Labelme. The masks for each image were drawn manually and saved into json (JavaScript Object Notation) format. These were then converted into a machine learning readable (binary) format and combined into one under the name "annotations" (the correspondent code is given in the Appendix) or using the online labelling tool, makesense.ai.

Using bounding boxes is difficult when annotated objects overlap. Image segmentation is the process of breaking an image in multiple segments. Every pixel within the segment represents a semantic label. It helps to recognise an object's attribute easier, thus it can provide more accurate results.

However, the drawback in using image segmentation is that it is time-consuming, and it is prone to human errors, especially taking into consideration the exhaustion of the annotator after labelling multiple images.

The datasets for both models are divided into three folders: training, validation and test. The main emphasis in developing the microplastic dataset was given to obtaining images with different backgrounds and different resolutions. The purpose was to train the models under real-world terrestrial and aquatic sample images, where MPs can be found.

2.2. Model training

2.2.1. YOLOv7 model

YOLOv7 is an accurate and fast updated version of the YOLO family of models, released in 2022 [78]. YOLO employs convolutional neural networks (CNN), with the algorithm requiring a single forward propagation through a neural network to detect objects. The CNN is used to predict various class probabilities and bounding boxes simultaneously. Essentially, YOLO applies a single neural network to the full image, which is divided into regions and predicts bounding boxes and probabilities for each region. The model defines semantic classes (in this case, categories of microplastics, such as fibres over a dataset of relevant images, which are annotated with bounding boxes identifying objects of those classes.

The efficiency of the model relies on:

- **Extended Efficient Layer Aggregation (E-ELAN)**: The final layer aggregation is a modification of the Efficient Layer Aggregation (ELAN), which uses group convolution to expand the channels and cardinality of the computational block. The E-ELAN applies the same channel multiplier and group parameter to all computational blocks in a computational layer without destroying the original gradient path. So, the feature map from each block will be shuffled into group size and concatenated together.
- **Model Scaling**: The previous YOLO models required adjustments to model attributes and scales to meet the inference speed requirements. In YOLOv7, scale the network depth and width in concert while concatenating layers together. Using this method, the model can keep to the optimal while scaling different sizes.

YOLOv7 manages to use optimal amalgamation of techniques from Bag of Freebies [79] and Bag of Specials [80] along with its architecture design, which provides reliable results from a conventional GPU. YOLOv7 employs a planned re-parameterised convolution technique within the model ensemble enabling the training of various identical models with different training data. The model training is broken up into multiple modules and the outputs are ensembled to obtain the final model. Finally, the authors of YOLOv7 added in the head an auxiliary head before the lead head. The head is responsible for the final prediction and with the assistance of the auxiliary head, the model learns better.

For this study, YOLOv7 model was trained using Google Colaboratory (Colab) with a Tesla T4 GPU. For the model, 8 workers were used, which are the number of subprocesses to parallelise during the training. The training was run for 200 epochs, which is the number times that the learning algorithm will pass through the training dataset. The number of epochs is normally high, to allow the algorithm to run until the error from the model has been minimised. The dataset size requires the use of batches, which determine the number of samples processed before the model updates. This was set as 16. The whole training process took less than 3 h to complete.

2.2.2. Mask R-CNN model

The Mask R-CNN model was deployed in 2017 and is the extended version of the Faster R-CNN model. R-CNN (Region-Based Convolutional Neural Network) uses bounding boxes across object regions. It evaluates convolutional networks independently on all the Regions of Interest Pooling (RoIPool). This is an operation for extracting small regions for detection and segmentation task, to classify multiple image regions into the proposed class and bounding box regression. RoIPool is an operation for extracting a small feature map from a Region of Interest (RoI).

In this study, Mask R-CNN with a ResNet-101 pyramid network as backbone [81] was utilised because it is based on image segmentation, a process of partitioning of a digital image into multiple segments, a set of pixels. The advantages of Mask R-CNN are the simplicity to train and the efficiency, as it adds a small computational head, enabling a fast system and rapid experimentation.

The implementation of the model is based on the existing open-source code by Matterport Inc released under an MIT license. The code works with the open-source libraries Keras and Tensorflow, which were used in Google Colab in this project. In 2020 Google released the new version of Tensorflow and Mask R-CNN needed major changes to be able to be implemented. Mask R-CNN was not compatible with the new version of Tensorflow, thus parts of the code needed changes to be able to work.

The model uses the weights from pre-training on the MS COCO (Microsoft Common Objects in Context) dataset. In total, the model was trained in 200 epochs and with a batch size of 16 for the specific dataset.

On Mask R-CNN, several changes were considered essential to improve the performance of the model and ensure its suitability for microscopic photos. Based on the study on cell instance segmentation [82], the RPN (Regional Proposal Network) anchor sizes were reduced and the number of anchors was increased, since fibres are small particles and they can be found in any part of the images.

2.3. Model validation and evaluation

The model was validated on images which were not part of the training dataset. This data set consisted of 35 images from different cameras (microscopes and mobile phone) and environments (bottled and environmental water);.

1.1. 10 were acquired with a Nikon microscope from bottled water samples with a white background.
1.2. 10 were acquired with a TOMLOV DM9 microscope from environmental water samples with a white background.
1.3. 10 were from environmental samples obtained with a TOMLOV DM9 microscope and a brown background.
1.4. 5 were taken with the mobile phone's camera (iPhone XR, 7-megapixel) from environmental samples and bottled water.

To evaluate the model's ability to handle new data, images that were previously unknown to the model (unseen during training) were used for testing. These unknown images were treated in a manner consistent with the training set to ensure a precise and fair comparison (Section 2.1.1). Specifically, the evaluation included images of treated environmental water samples from different environments (rivers, estuaries, and oceans) alongside untreated bottled water samples. Images from untreated bottled water samples provided a different matrix for model evaluation. By including these images, the models were tested across a variety of environmental matrices, thereby assessing their robustness (Fig. 2).

The accuracy of the model was evaluated against the number of microplastic fibres the models correctly detected based on the μFTIR identification detailed in 2.1.1.

2.4. Model deployment

To test the application of the model to environmental water samples, sea water (n = 11) samples were collected during May 2022 from locations in Seyðisfjörður (65.292449, −13.896733), and Loðmundarfjörður (65.356993, −13.819430) in eastern Iceland. Sampling sites were selected strategically along the coastline to cover various geographies (including, river mouths, sandy beaches, and rocky shores), and varying proximity to human activities which were likely to produce a varied range of sample qualities and microplastic concentration ranges allowing the models to be applied to and tested on data collected and processed for standard research purposes. Additionally, the dataset was also used to evaluate the accuracy and efficiency of the human eye alongside the two machine learning models.

Surface water was sampled using a silicone tube and peristaltic pump connected to a filter setup which included a GF/F filter (with a nominal pore size of 0.7 μm and a diameter of 47 mm). The setup was chosen to minimize potential contamination through contact with the air. To further reduce contamination, the system was purged with water from the sample site prior to insertion of the filter. A total of 4 litres of water was collected at each site, with the filter immediately wrapped in tin foil for subsequent analysis. The laboratory analysis was conducted as described in *Section* 2.1.1, with total microplastic count divided by the number of litres (4) to provide a concentration.

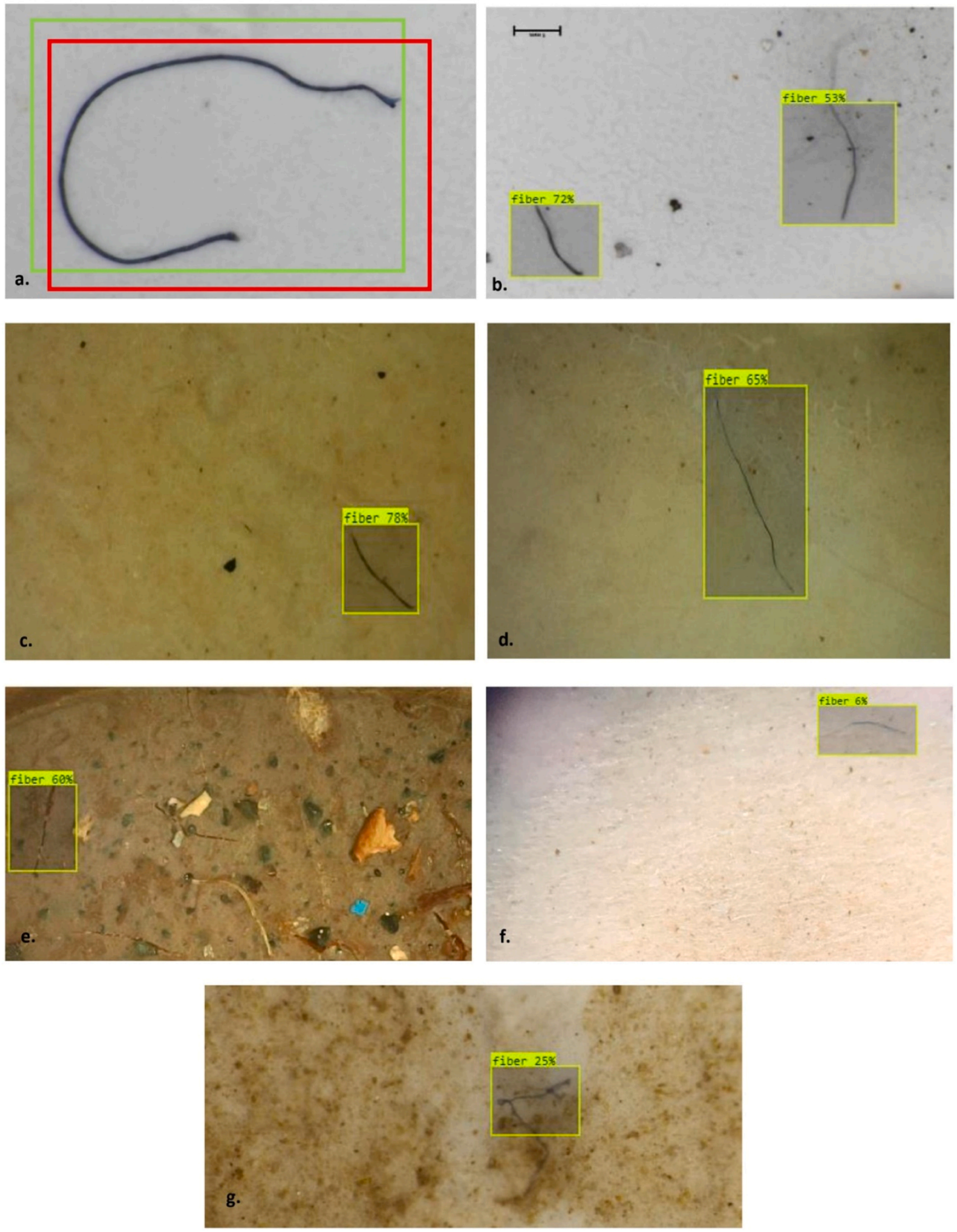

Fig. 2. a) Ground truth box in green colour and Detected box in red colour; b) Predicted results on various test images using YOLOv7 model for photograph taken with a Nikon 16.25 megapixel camera on white background, true positive, (c) and (d) photos taken with a TOMLOV microscope on brown and green background, true positives and (e) photo taken with a TOMLOV microscope. F and g show false positive, f. and g. predictions for images taken using a mobile phone (iPhone XR).

3. Results

3.1. Model evaluation

The original model of YOLOv7 is trained and evaluated with images where the objects are much bigger than microplastics (< 5 mm). Thus, the original model achieved low performance (40 %) in detecting small particles.

However, in this study, the modified YOLOv7 model with the new training dataset performed better. For YOLOv7, mean Average Precision (mAP) was used as a primary metric. The mAP reflects the model's precision with Intersection over Union (IoU) threshold (IoU=0.50), which measures how closely the predicted bounding boxes correspond to the ground truth. An IoU of 0.50 indicates that the detected object overlaps 50 % with the ground truth object, considered a match, while 0.95 IoU denotes almost perfect overlap. However, for Mask R-CNN, which also provides instance segmentation, we not only considered mAP but also the mean IoU (mIoU) for the segmented masks, providing a pixel-wise accuracy assessment. The use of mAP alone for Mask R-CNN would not fully capture its segmentation performance, hence the inclusion of mIoU as an additional, crucial evaluation metric.

The mAP in YOLOv7, which depicts the overall accuracy by comparing the ground-truth bounding box to the detected box, reached 71.4 % (Fig. 2a, and Fig. 3). The model's precision was 69.8 %, which shows how reliable the model is at detecting objects without any mistakes. The model calculates the ratio between the number of correctly detected samples (True Positive) to the total number of samples. It classifies them as True Positive, if the fibre is correctly classified or False Positive, if the model recognises incorrectly an object as fibre. The recall was calculated 74.1 %, which is the ratio between the number of positive samples (True and False Positives) to the total number of positive samples. The model has a slightly higher percentage of recall than

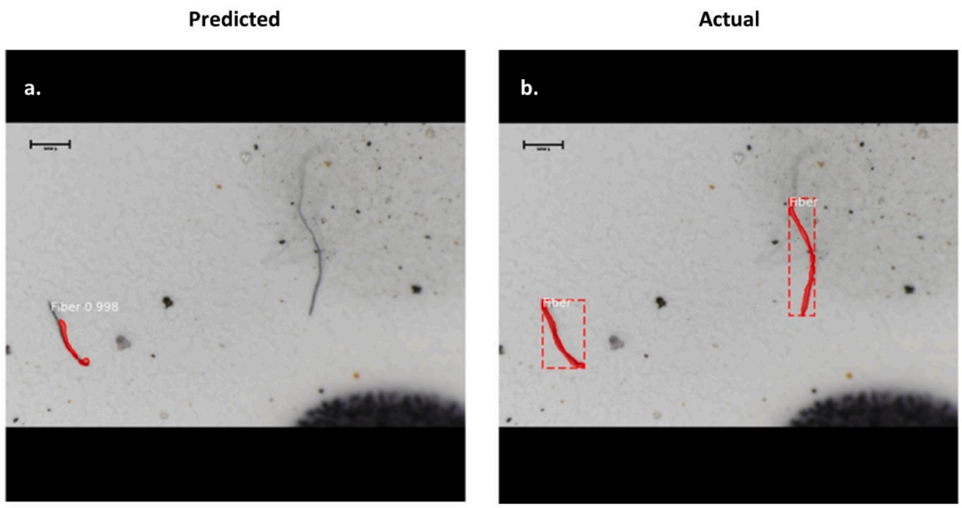

Fig. 3. a) Image with the predicted microplastic fibre using Mask R-CNN vs image with actual microplastic fibres using Mask R-CNN model (b).

precision, thus the model classifies the majority of the positive samples correctly.

When detecting fibres on images from the mobile phone, the confidence level (the number that shows how confident the model is of a result) was less than 25 %. The low confidence level can be due to either blurred images taken by the operator or lack of training of similar images.

The Mask R-CNN model obtains an average mask intersection over union (mIoU) of 49.09 % (Fig. 3 and Fig. 4). The main limitation of this approach is the scarce variety of images. Visual recognition models can exhibit biases towards the training dataset they are trained on. These biases arise due to several factors, including quality of the training data and composition. For example if facial recognition system is trained mainly on data from one demographic group, it may perform poorly on other groups [83]. To mitigate biases in the model, it is necessary to collect diverse training data; the training dataset needs to encompass a broad range of variations, such as different environmental backgrounds, and/or lighting conditions. Furthermore, reviewing image data augmentation strategies could assist to improve and add more images. Detection errors appeared in some tested images, which were likely due to different backgrounds and lower image quality. Overall, addressing biases in visual recognition models requires a holistic approach that encompasses diverse and representative training data to ensure fairness.

In addition, the incompatibility of Mask R-CNN model with the current version of TensorFlow and the dataset of the images were the principal issues of the low performance. Mask R-CNN is not easy and flexible to use with the new version of TensorFlow. To perform some tasks, it needs TensorFlow 1.14.0 which is not compatible with Google

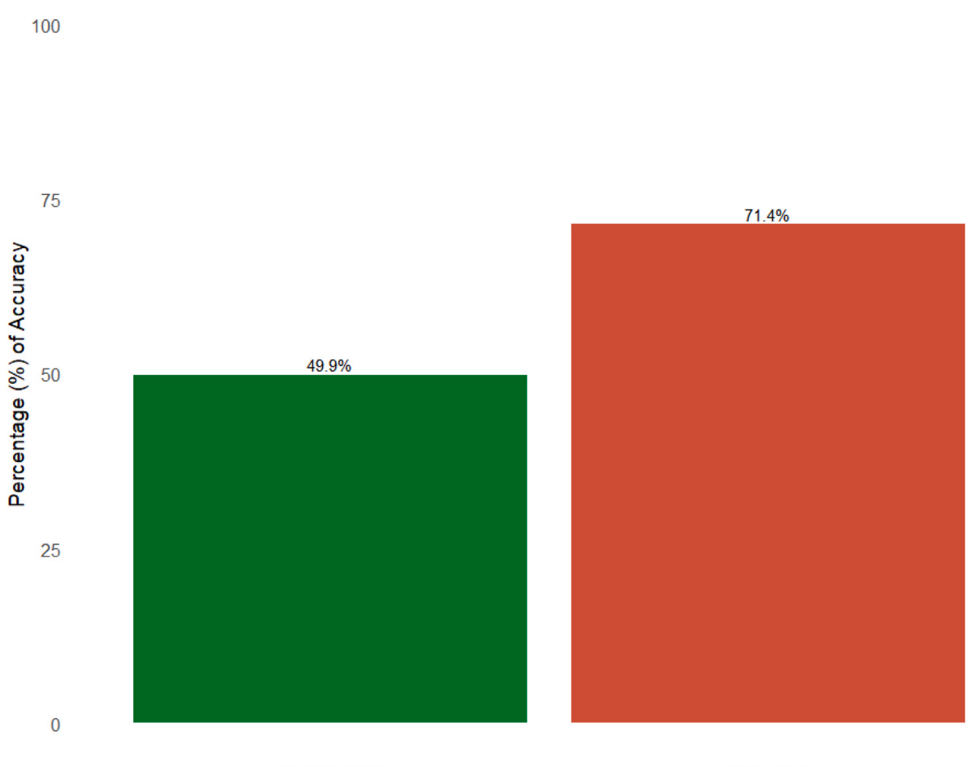

Fig. 4. Accuracy of the YOLOv7 and Mask R-CNN on identification of fibres in the test dataset.

Colab and Jupyter Notebook. Overall, the code was adjusted, and the Mask R-CNN model underperformed without and with the pre-processing of images resulting in the mIoU of 49.9 %.

The low accuracy regarding the fibre detection can be due to various factors concerning the training dataset. These factors may include the limited diversity of fibre types and shapes in the dataset, potential imbalances in the number of images per class, and variations in image resolution, all of which could contribute to the model's difficulty in accurately detecting certain fibres. It is vital that the data for each class of microplastics (fibre, fragment, pellet, rod) is balanced – the number of labelled images should be similar [84]. The quality, quantity and diversity of the training data determines the performance of the models.

3.2. Deployment: monitoring of natural waters in Seyðisfjörður, Iceland

YOLOv7 identified microplastic fibres in all but one environmental water sample from Seyðisfjörður. Microplastic concentrations ranged from 0 to 2 MP/l, with the lowest identified concentrations found in the water samples taken further from the shore (Fig. 5).

Deploying the models on environmental water samples provided the opportunity to evaluate both the efficiency and accuracy of microplastic fibre detection method using the models, but also using the human eye. The accuracy, in this case, refers to the proportion of true positives (correctly identified microplastics) out of the total number predictions made by the model or human observer versus fibres identified as plastic using a μFTIR. For YOLOv7, accuracy was quantitatively evaluated using mAP 0.50, providing a measure of the model's detection precision with IoU threshold of 0.50. In comparing human detection observations with YOLOv7, the study primarily focused on the success rate of correctly identified fibres and the time efficiency of each method. While the metrics used for human detection and YOLOv7 differ due to the qualitative nature of human analysis, both assessments aim to highlight the comparative effectiveness and efficiency of automated detection methods in microplastic research.

The human eye, despite its rapid analysis speed of 14.53 s per fibre, has a limited detection success rate of 60.5 %, with and without pre-treatment. On the other hand, the YOLOv7 algorithm proves to be efficient in terms of time, needing only 0.40 s per fibre. Alongside this, its accuracy is higher at 71.4 %, while Mask R-CNN's accuracy is 49.9 %, detecting 0.60 s per fibre (Fig. 6 and Fig. 7a). However, there is decrease in accuracy on the detection of non-treated samples to 66 % and 45 %, respectively (Fig. 7b).

In terms of total detection counts for all Icelandic test samples, YOLOv7 detects the highest number of fibres (123), followed by Mask R-CNN (110), and human eye (109) (Fig. 8). Nonetheless, YOLOv7, Mask R-CNN and human eye are subject to certain limitations, such as the possibility of counting the same fibre more than once or misidentifying a natural fibre as a plastic one. Erroneous counting has potential to impact microplastic estimation through all methods. Identification with the human eye is prone to multiplication in counts or missing particles altogether [68]. Additionally, it is known that due to the tedious nature and time required, error rates typically increase with time. Automated methods such as those highlighted in this stud are more likely to double count due to the quality of the image or in cases where particles are obscured by non-plastic debris. E.g. Fig. 3b shows a fibre where ~50 % is in focus. There is potential, that should this occur mid fibre with a subsequent return to focus, the algorithm may identify this as 2. This however was not seen in this study. Overall, the errors introduced this way are likely smaller than those through sampling and sample treatment [85,86].

Building on this, the next analytical step following microplastic identification, is the application of micro Fourier-transform infrared spectroscopy (μFTIR) to verify and ascertain the composition of the detected microplastic fibres. This method is vital for accurately differentiating among various plastic types. In this process, μFTIR has confirmed that out of the fibres detected by the human eye, Mask R-CNN and YOLOv7, 66 are plastic. The incorporation of μFTIR is expected to refine the veracity and reliability of the findings, providing a more nuanced understanding of the types of microplastic pollution in Icelandic aquatic environments.

4. Discussion

Currently, the assessment of microplastics in the environment

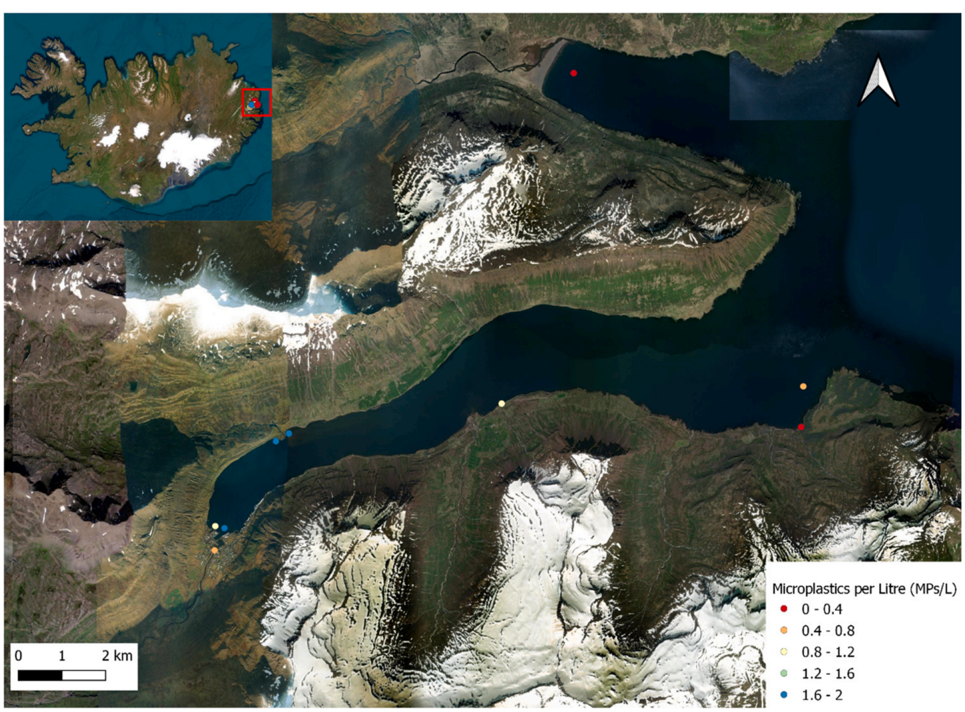

Fig. 5. Locations of surface sea water samples within Seyðisfjörður, Iceland. Symbol size reflects MP concentrations (World Imagery; Source: Esri).

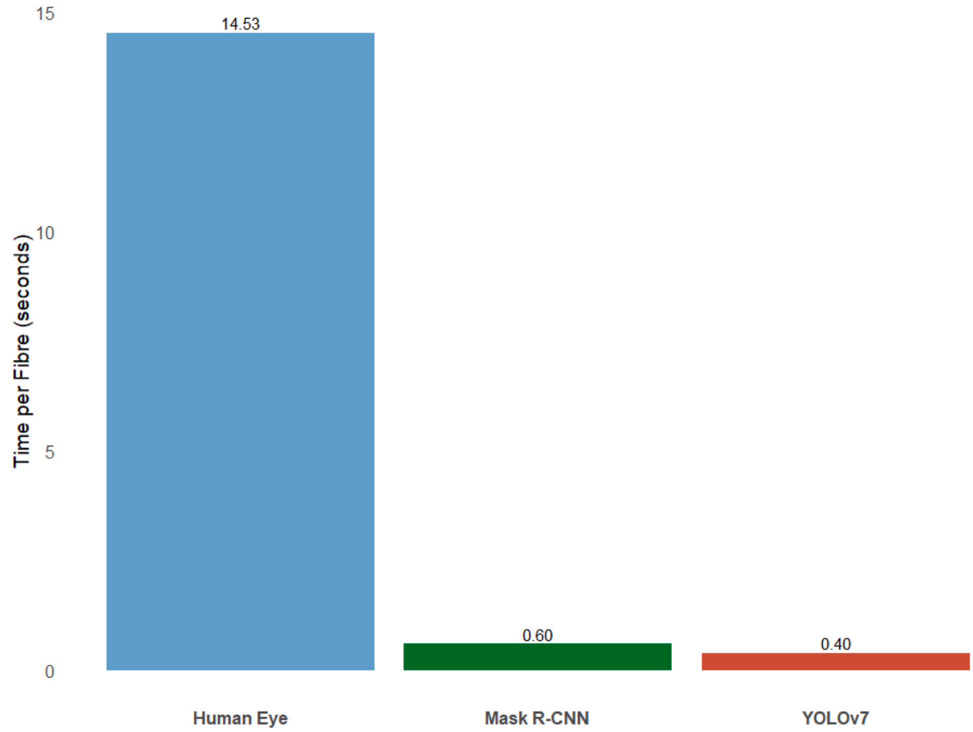

Fig. 6. Time required per fibre for two different microplastic detection methods: Human Eye and YOLOv7 with a significant difference in processing speed (chi.test: p-value= 0.0002553).

consists of a series of time consuming, resource demanding and error prone processes, consisting of; sampling, extraction, visual detection, quantification, and spectrometric identification. Despite attempts to automate these processes with the view to reducing the costs, effort, and errors, microplastic detection and identification still requires time, and specialised expertise and equipment. This hinders their regular monitoring and underscores the ongoing challenges in addressing this environmental concern comprehensively.

There is therefore a clear requirement for a tool which will provide fast, accurate results. Thus, this paper evaluates two deep learning models, YOLOv7 and Mask R-CNN, which may provide an effective solution for the investigation of MPs in environmental samples. YOLOv7 and Mask R-CNN models were trained to detect fibres, which are the most abundant type of microplastic in the environment and the most challenging, as they can be in diverse forms and shapes, tangled or attached with other particles.

Experimental results demonstrate that the performance of YOLOv7 was high. Deploying YOLOv7 in a custom dataset was relatively easy and did not require many changes to adapt the original code. In addition, the training dataset in this study was limited (200 images) in comparison to other models, but YOLOv7 and Mask R-CNN performed efficiently regardless. In contrast, Mask R-CNN, although having been previously used successfully for microplastic quantification [48,49], proved to be more challenging in this task. It requires a high level of programming knowledge and is not as user-friendly, which can be a significant barrier for many potential users.

Mask R-CNN underperformed in this task compared with YOLOv7. An accuracy of 49.9 % for Mask R-CNN is lower than other Mask R-CNN models uses [63,87], indicating that the model does not perform well for this dataset. Due to the recent incompatibility issues with the updated version of TensorFlow, a temporary solution involved reverting to a previous, stable version, while actively monitoring TensorFlow's development for future updates that resolve these technical challenges mentioned in *Section* 4.

Overall, the use of object detection models for detecting microplastics from low resolution images gives promising results compared to the traditional, time-consuming techniques. These models, especially YOLOv7, can process images in seconds with no requirement for high performance computing, and can be deployed easily on local workstations or cloud computing platforms, with little coding knowledge. The models are accessible and user-friendly for every level of computer user. These models have potential uses across industries that heavily rely on visual data, (e.g. environmental companies), and in academia.

The use of these models can assist in quantifying microplastic fibres rapidly, and also has a place in exploration of microplastic extraction techniques and during development of methods to degrade microplastics. Additionally, combining vision recognition with environmental data analysis can provide a more comprehensive understanding of microplastic pollution. However, although vision recognition is a valuable tool, it should be used as part of a broader approach to tackling the issue of microplastic pollution. In the future, the main goal should be the updating of the dataset of images with different categories of microplastics, so that the models can classify any type of microplastics. Testing the model on environmental samples from Iceland emphasises the ability of the model to maintain accurate detection regardless of variations in lighting conditions or resolution, and cements its potential for real-world applications, where environmental conditions can be unpredictable and diverse. Overall, the application of YOLOv7 in environmental sample analysis offers the potential to enhance the efficiency, accuracy, and cost-effectiveness of the process. By automating tasks, reducing human intervention, and improving data analysis, it can help researchers better understand environmental dynamics and support informed decision-making for environmental conservation and management.

The results obtained from Seyðisfjörður, Iceland, demonstrate the utility of advanced automated systems such as YOLOv7 in improving the efficiency of microplastic monitoring efforts and similar results can be achieved in other regions with complex water samples. The model's architecture is designed to handle variability in sample characteristics, which are common across different environmental contexts, such as variations in background noise and/or presence of other materials (e.g. organic matter or sediments) The comparative analysis revealed that

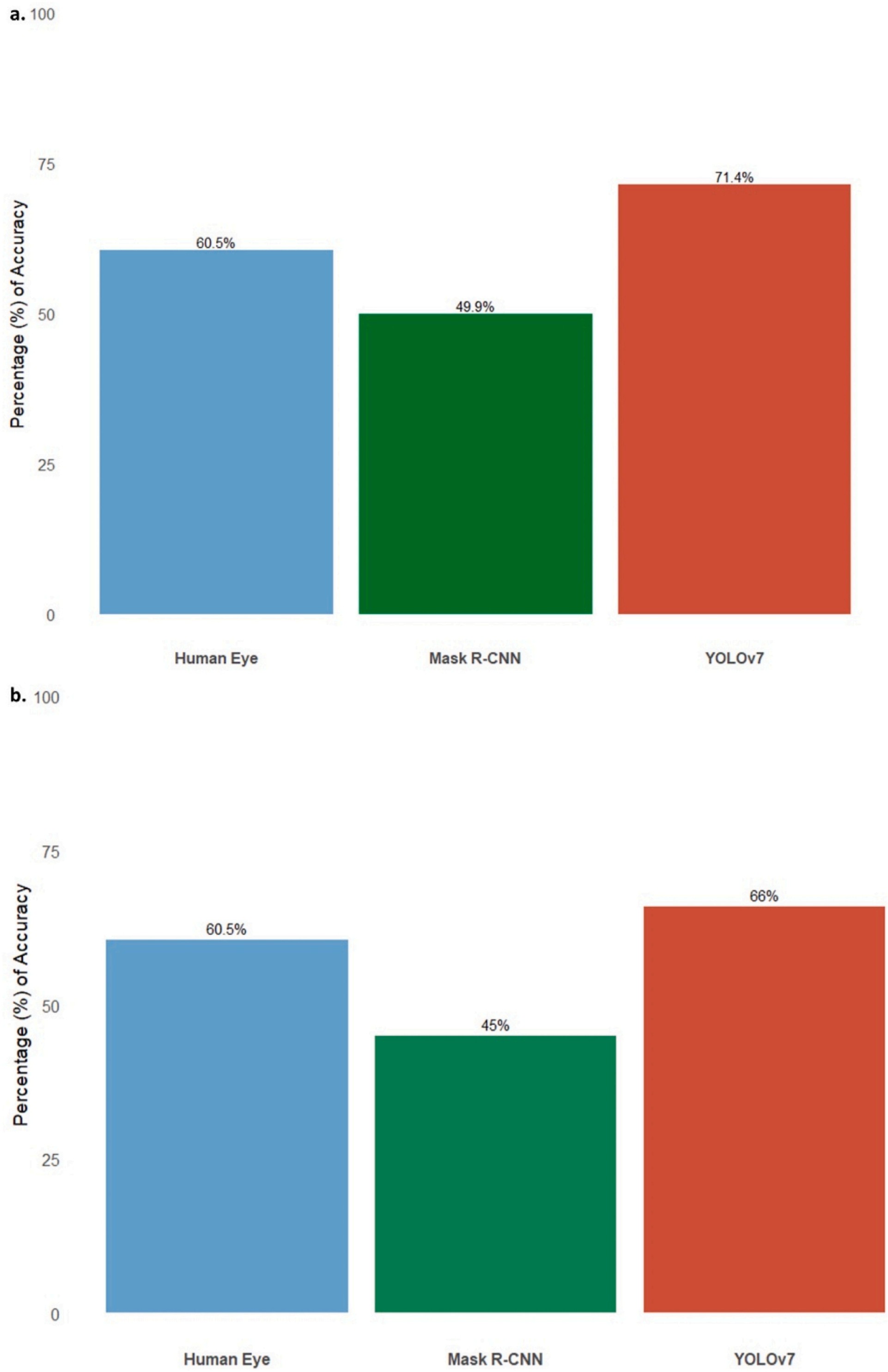

Fig. 7. a) General accuracy (%) for three different microplastic detection methods: Human Eye, Mask R-CNN andYOLOv7; b) Accuracy (%) for three different microplastic detection methods: Human Eye, Mask R-CNN, and YOLOv7 but for only sampled without pre-treatment.

YOLOv7's rapid detection rate could significantly improve methodological efficiencies. However, the study also underscores the relevance of human analysis as a baseline, which, despite its lower success rate, is crucial for validating automated detection methods and ensuring their accuracy. Incorporating μFTIR spectroscopy as a key step in the analysis underscores the necessity of precise methods in the complex task of assessing microplastic pollution. The variance in microplastic quantities among the different sites in Iceland highlights the influence of local environmental factors, emphasizing the necessity for a nuanced approach to environmental monitoring. This approach requires advanced detection methods that are not only time-efficient but also precise. By streamlining analysis through automation, reducing the need for human intervention, and refining data interpretation, this model facilitates a deeper understanding of environmental microplastic pollution.

The primary limitations identified in this study include the reduced

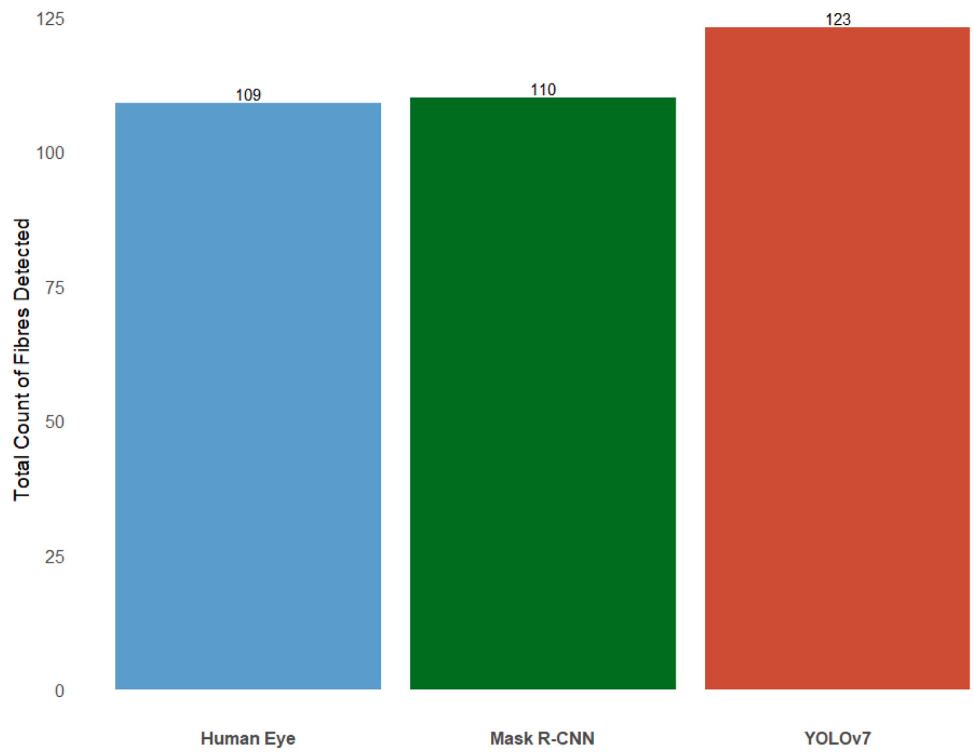

Fig. 8. Total count of fibres detected using three different microplastic detection methods: Human Eye and YOLOv7.

accuracy of the YOLOv7 model compared to more complex models, the potential for misclassification in varied environmental conditions, and the challenges of generalising results across different sample types due to the controlled nature of the training datasets. These limitations imply that while YOLOv7 offers speed and efficiency, it may yield a higher rate of false positives or negatives in complex environments. To counter these issues, future work could involve enhancing model training with more diverse datasets, implementing post-processing techniques for refined detection. Continuous validation and retraining of the models with new data are crucial to maintain their effectiveness as new challenges in microplastic detection arise.

This study leverages YOLOv7 and Mask R-CNN models for the detection of microplastic fibres, distinguishing itself from existing methods in both technological advancement and user accessibility. While recent studies employ Raman spectroscopy and deep learning for microplastic classification and demonstrate the growing use of sophisticated techniques, they required more time, specialised knowledge, increased sample processing, and equipment and thus, have limited broader application [48,88-90].

While high-accuracy models for microplastic detection exist, their practical application is hindered by a critical limitation: a lack of user-friendliness and the high costs associated with their deployment. Despite their technological sophistication, many of these deep learning models, including microplastic detection, demand specialised knowledge, rendering them inaccessible to a wider research community [91-93].

In contrast, our approach achieves a balance between accuracy and accessibility. This study's models attain competitive accuracies, especially YOLOv7 with 71.4 %, comparable to high-accuracy methods, like U-Net and VGG16 neural networks [94,95]. However, our models stand out in their ease of use and the level of programming needed is minimal. The access to cutting-edge research tools allows to a wide range of researchers and practitioners to contribute to the field of microplastic pollution.

In the rapid advancing field of machine learning, new models and updates emerge regularly, offering enhanced capabilities and performance. While this study employed YOLOv7 due to its cutting-edge accuracy and reliability at the onset of this research, it is important to note that subsequent iterations, such as YOLOv8 [96] and YOLOv9 [97], have released. Nevertheless, the selection of YOLOv7 was deliberate, allowing for the use of well-established and validated model to ensure the robustness of the results within the time frame of this study. Future studies could explore the use of more recent YOLO versions to potentially enhance detection methodologies further [96,98].

This research seeks to build upon the foundational work established by previous studies, including those employing advanced methodologies such as MATLAB for image analysis[40] and holographic imaging techniques[43]. While these approaches have significantly contributed to the understanding and capabilities in detecting microplastic pollution, there exists a parallel need for methodologies that are not only cost-effective but also user-friendly, without substantially compromising on analytical performance.

The introduction of models such as YOLOv7 constitutes a significant progression in the field, merging high analytical performance with enhanced user accessibility and cost efficiency. These models represent a crucial development for efficient and rapid processing, which is essential for real-time analysis in the context of global microplastic pollution challenges. Consequently, they serve as a vital tool, broadening the accessibility of advanced research methodologies to researchers with varying levels of computational skills, from the minimum programming knowledge to the highest one. The merge of user accessibility with robust analytical capabilities marks an advancement in enhancing environmental monitoring approaches.

5. Conclusions

Addressing microplastics in the environment involves multiple steps (sampling, extraction, visual detection, quantification, chemical identification) requiring expensive equipment and time, hindering large-scale analysis. Recent advancements aim to increase efficiency and reduce costs, yet challenges persist due to the need for specialised expertise and equipment. This paper proposes a deep learning model, YOLOv7 to address these issues. YOLOv7, a new addition to microplastic quantification research, was compared and performed better than the previously used Mask R-CNN.

Both models were trained to detect microplastic fibres, which are abundant and challenging due to their diverse forms. YOLOv7 achieved high performance, was easy to deploy, and worked well with a limited dataset (200 images), while Mask R-CNN underperformed with 49.9 % accuracy due to TensorFlow incompatibilities.

Object detection models such as YOLOv7 show promising results compared to traditional techniques, by processing images quickly without needing high-performance computing. They are accessible and user-friendly, suitable for both industrial and academic applications. In industry, this model can quantify microplastic fibres, while academic can explore extraction techniques, etc.

Future efforts should focus on updating image datasets to classify various microplastics. Testing on Icelandic environmental samples demonstrated the YOLOv7 model's robustness in diverse conditions, cementing its potential for real-world applications. Overall, YOLOv7 enhances the efficiency, and cost-effectiveness of environmental sample analysis, supporting better understanding and informed decision-making for environmental conservation and mitigation.

Environmental implication

Microplastic pollution poses significant environmental threats, including contamination of aquatic ecosystems, ingestion by marine organisms, and potential entry into the human food chain. Advanced detection methods like YOLOv7 offer rapid and accurate quantification of microplastics, enhancing monitoring efficiency. These models facilitate better understanding of microplastic distribution and impacts, aiding in targeted mitigation strategies and informed decision-making for environmental conservation.

CRediT authorship contribution statement

Jonathan James Dick: Writing – review & editing, Validation. **Konstadinos Kiriakoulakis:** Writing – review & editing, Validation. **Timothy Lane:** Writing – review & editing, Validation. **Ian Walkington:** Writing – review & editing, Validation. **Stamatia Galata:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation.

Declaration of generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author(s) used Scholar.AI in order to act as a grammarian and avoid language mistakes. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Stamatia Galata reports administrative support, equipment, drugs, or supplies, statistical analysis, travel, and writing assistance were provided by Liverpool John Moores University. Stamatia Galata reports a relationship with Liverpool John Moores University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data will be free and aceessible through the link in Github.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jhazmat.2024.135956.

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