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Microplastic Classification and Quantification in Water Bodies

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ABSTRACT

Microplastic pollution poses a dangerous, "invisible" threat to both aquatic ecosystems and human health. Most studies rely on complex chemical methods for microplastic detection. However, by combining machine learning algorithms with a Raspberry Pi, this research paper proposes an innovative approach to classifying and quantifying microplastics. We developed a low-cost, portable prototype device that captures microscopic images for in-situ microplastic detection. Our algorithm makes use of Convolutional Neural Networks (CNNs) to recognize and categorize microplastics in their environment. In addition to automating and accelerating the detection process, CNNs capture important visual traits that allow precise categorization and quantification. The model's remarkable performance, with a 97% accuracy rate, highlights its potential for classifying and measuring microplastics in aquatic settings. In the future, this device could lend itself to other such significant environmental monitoring needs, and to larger-scale microplastic detection.

Index Terms—Microplastic, Detection, Classification, Machine Learning, CNN

INTRODUCTION

Every year, over 400 million tons of plastic are generated, of which >8 million tons are dumped into the ocean [1]. Plastics do not degrade easily; they persist for over 100 years and thus have the potential to accumulate and contaminate their environments. In the past decade, microplastic pollution has emerged as an "invisible" threat to ecosystems and human health.

Microplastics i.e. plastics <5mm long [2] are formed either by design or by the gradual fragmentation of plastic waste [3].

Microplastics are highly ubiquitous – they have been found in marine environments, soil, and even lung tissue [4]. They collect in sediment and water columns in aquatic environments, where they act as harmful chemical reservoirs for heavy metals and pesticides. They pose a risk to human health, behaving as endocrine and immune system disruptors [5].

Detecting microplastics without labour-intensive techniques such as visual classification, chemically advanced techniques such as Raman Spectroscopy, or equipment such as microscopes is a challenge, given their minute size.

However, developments in artificial intelligence in the last decade have opened up new avenues for microplastic detection. Convolutional Neural Network (CNN) is a straightforward classification algorithm that can be modified for object detection tasks in photos and videos.

CNN can effectively detect and categorize microplastic particles in water samples based on their characteristics, such as size, shape, and texture, by utilizing machine learning algorithms. CNN, in contrast to deep learning techniques, does not need a protracted training phase, which makes it particularly useful in circumstances with little labelled training data. This research paper focuses on deploying an innovative, low-cost microplastic detection device based on the CNN framework and subsequently analyzing its effectiveness. The key objectives of this study can be summarized as follows:

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- Proposing a deep-learning model for easy identification and classification of microplastics
- Developing a portable, in-situ, low-cost & real-time microplastic detection device that can be used on the field

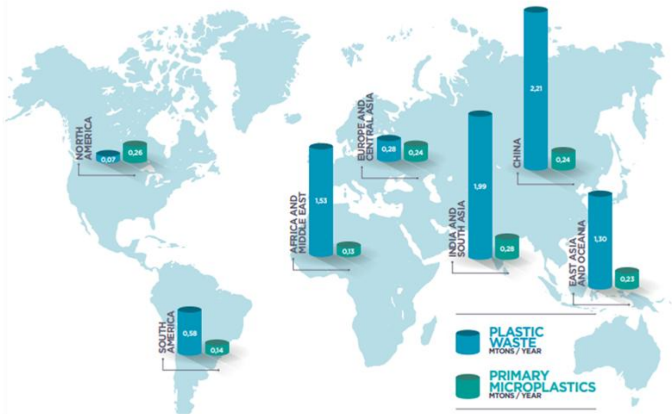

Fig 1 Plastics and Primary Microplastics by Region

(Image Credit: J. Boucher and D. Friot, "Primary microplastics in the oceans: A global evaluation of sources," IUCN, Feb. 2017, doi: https://doi.org/10.2305/iucn.ch.2017.01.en.)

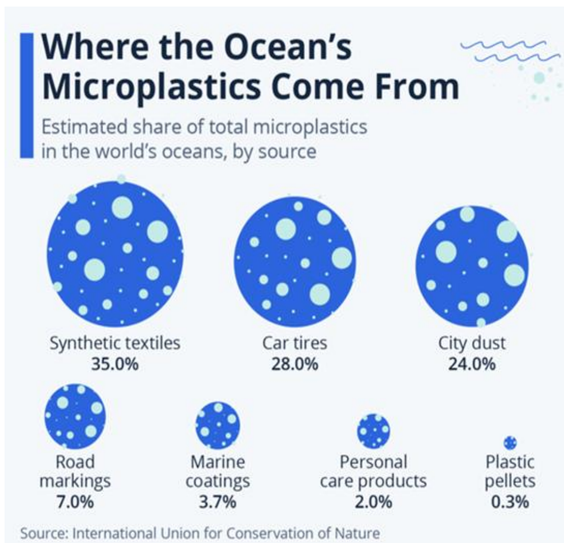

Fig 2: Sources of Primary Microplastics

(Image credit: M. Armstrong, "Infographic: Where Do the Oceans' Microplastics Come From?," Statista Infographics, Aug. 11, 2022. https://www.statista.com/chart/17957/where-the-oceans-microplastics-come-from/)

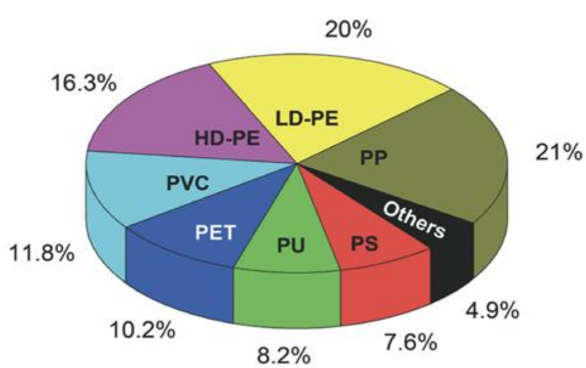

Fig 3: Plastic production by polymer type

(Image Credit: M. Malankowska, C. Echaide-Gorriz, and J. Coronas, "Microplastics in marine environment – sources, classification, and potential remediation by membrane technology – A review," Environmental Science: Water Research & Technology, 2020, doi: https://doi.org/10.1039/d0ew00802h.)

LITERATURE REVIEW

Microplastics have been found everywhere. Filho et al. [6] detected microplastics in milk using micro-Raman technology involving enzymatic and digestion steps. They categorized the microplastics detected based on polymer type. Similarly, Ragusa et al. [7] discovered microplastics in the human placenta using micro-Raman spectroscopy. Filter membranes were inspected, morphologically characterized, and analyzed using Raman Microspectroscopy. The spectra were compared with those in the SLOPP Library of Microplastics and KnowItAll software, with similarities of over 80 of the Hit Quality Index (HQI) considered satisfactory. Zhang et al. [8] detected microplastics in deep-sea sediments in the western Pacific Ocean using micro-Fourier-transform infrared spectroscopy, which involves comparing the absorption spectra of infrared radiation in samples. They discovered that the most commonly detected polymers were poly(propylene-ethylene) copolymer (40.0%) and polyethylene terephthalate (27.5%). Cocciaro et al. [9] meanwhile, used infrared photo-diode sensors to detect floating microplastics (polyethylene and polyurethane) with an approximate ~90% accuracy. These techniques are, however, expensive, fairly time-consuming, and difficult to scale up.

There have been recent advancements in using machine learning to detect microplastics – per Lin et al., [10] artificial intelligence is confirmed to improve the efficiency and accuracy of microplastic detection.

In a study conducted by Yurtsever et al., [11] they developed a CNN model using GoogLeNet architecture to detect microplastics. They created a dataset using microscope images in a number of pure and wastewater environments. The model was trained on this dataset of 42,928 images and yielded a rather high accuracy of 89% for microbeads in wastewater and 97% in pure water. Meanwhile, Silva et al. [12] utilized a slightly different approach for detecting and classifying microplastics based on polymer type. They used Fourier Transform Infrared Imaging Systems to detect and machine learning models such as Partial Least Squares Discriminant Analysis (PLS-DA) (multivariate classification technique mathematically correlating independent matrix to parameters of interest) and Soft Independent Modeling of Class Analogies (SIMCA) (focused on analogies within a class) to classify. They found that the PLS-DA model was far superior to the SIMCA model as it was able to provide a more holistic understanding of the plastic classes. In a study by Chaczko et al., [13] they built a Neural Network (NN) using tensorflow. Interestingly, they trained their ML model on hyperspectral images of textiles rather than microplastics, in which samples were considered "suspicious contaminants". Their model achieved 95% accuracy, however, it is unclear how the NN will perform when given actual images of microplastics. Zhu et al. [14] used a deep-learning enabled holographic classification system; their HC-CNN showed superior performance when cross-validated against most other models (on the same dataset), except against the deep-transfer learning model by Zhu et al. [15] built on the CompNet network which showed great potential, especially for small, imbalanced datasets. In another study by Odei Garcia-Garin et al. [16] they used CNN models to measure floating marine macro-litter. They used aerial photographs to collect data and deployed a web-based application that enables users to spot FMML in images of the sea surface. The accuracy of cross-validation (done using 90% of the photos for training and 10% for testing) and image classification (performed using all the images for training and testing the model) was 0.81 and 0.85, respectively. However, the key difference is that FMML can be viewed without a microscope, hence creating a dataset is far easier. Wang et al. [17] developed an improved region-based convolutional neural network (R-CNN) model for identifying and detecting microplastics. The model uses residual network-50 as the backbone and feature pyramid networks (FPN) module for multi-scale target detection. The improved R-CNN model achieved an average confidence of 99% in detecting microplastic particles in marine environments. The model identified polystyrene microplastics accurately under various conditions.

Lorenzo-Navarro et al. [18] aimed to identify and classify microplastic particles into categories based on shape: lines, pellets, fragments, tar, and organic particles, and evaluate different machine-learning approaches. Images were captured using Epson Perfection V800 and the segmentation step used the Sauvola Thresholding Method, followed by feature extraction using Local Binary Pattern. 5 different classifiers were tested: K Nearest-Neighbour, C4.5, Support Vector Machine and Random Forest, and a cascade classifier which follows a sequential progression and uses all 4 classifiers. The cascade classifier was found to have the highest accuracy. As different texture features seem to negatively affect certain classifiers, it was advantageous to apply a multilayer cascade classifier. While their previous study evaluated different approaches, in another study by Lorenzo-Navarro et al. [19] they used a VGG-16 classifier model to classify microplastics.

The novelty lies in the fact that this architecture does not require microscopes or expensive equipment, instead microplastic detection can be carried out with a mobile phone alone, and can be applied to particles larger than microplastics. Their classifier yielded a higher accuracy than computer vision techniques and manual inspection. According to Zoe Moorton et al., [20] their CNN models can be used to successfully classify debris without disrupting aquatic life, particularly when using transfer learning on VGG-16. They utilized a binary classification to distinguish synthetic material from aquatic life using a unique collection of 1644 underwater photos. Grant-Jacob et al. [21] developed a real-time sensor based on the principles of scattering of light for detecting microplastics and salinity. It used a Neural Network with Raspberry Pi. While, in itself, it does not constitute a portable microplastic detection device, it has great potential for such a device.

Although previous work has established machine learning as a powerful tool for microplastic detection, a portable, real-time detection and classification device is yet to be developed. Hence, this research paper focuses on developing a CNN-based model in a portable Raspberry Pi device for detecting and classifying microplastics.

METHODOLOGY

The primary objective of this study is to develop and validate a cost-effective, portable system for the detection of microplastics in water samples. Microplastics can be classified on the basis of polymer types: HDPE, polyethylene, nylon, microbeads, polyurethane, and polystyrene. These microplastics come from a variety of products, including plastic ones, fabrics, and toiletries. All polymer types have been found in a variety of aquatic ecosystems, including lakes, oceans, rivers, etc. These bodies of water prove to be important research sites for analysing the extent of microplastic pollution. For example, lakes offer important insights into freshwater contamination, and ponds, which may be found in many different places, serve as localised markers of microplastic presence. To evaluate the environmental impact of microplastics in aquatic habitats and protect both ecosystems and human health, it is crucial to have a comprehensive understanding of their distribution and types.

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Table 1 Microplastics found in the number of Samples collected

Source of Sample	Microplastics found in the sample
Lakes	HDPE, Polyurethane
Ponds	Polyester
Rivers	Microbeads, LDPE
Creeks	Nylon,

First, ten contaminated water samples were methodically gathered from each location (lake, pond, river, creek) across Mumbai in glass test tubes. These samples were separated manually and then processed in the lab using spectroscopy to analyze the polymer type. The polymer types and sources are outlined in Table 1. Different mixtures of polymer samples and pure water and combinations of polymer samples and wastewater were placed under a microscope of 40x magnification. Images were captured for each sample. The collected data was then labeled using the Makesense.ai tool [22] and a CSV file was generated. The CSV file was then fed into the CNN Model.

CNN is a valuable deep-learning tool for object detection and image classification. This CNN model was built using the Keras framework as the basis of the code. The model includes key convolutional layers for feature extraction, max-pooling layers for downsampling, dense layers for decision-making, and dropout layers for regularisation. The dataset created from the microscope images was used to train our CNN model, including representing the training accuracy and training loss. A confusion matrix helps further evaluate the performance of the model further (Fig 8). The algorithm also identifies the density of microplastics in a given image through the following procedure: first, the images are converted from RGB to greyscale, thresholding is used to make binary masks, and contour detection is used to determine the density of microplastics inside a defined region of interest. It then generates time series plots and bar charts to help visualize the microplastic density on different days. This is a crucial component of a larger effort aimed at thorough microplastic data processing and visualisation via machine learning methods.

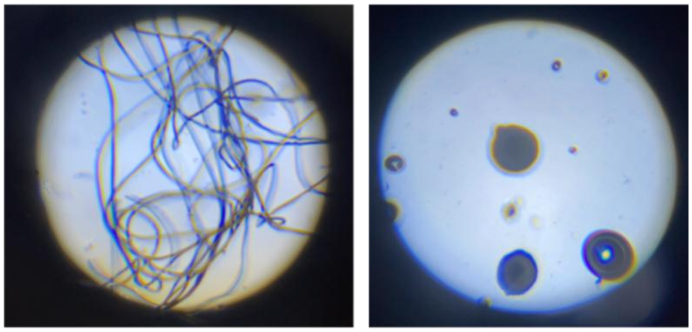

Fig 4 Polyester and Microbeads found in a sample collected from ponds and rivers

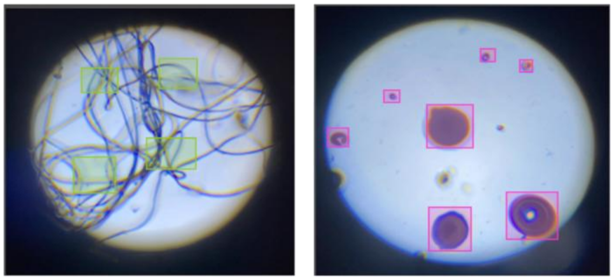

Fig 5 Annotated Images of Polyester and Microbeads

The device as shown in figure 6 consists of a 100-x zoom adjustable microscope. The CNN code is converted into a tflite file so that the inference can be deployed on a Raspberry Pi. the device and enclosed the 3.3 inch display that displays inferedreults and also log the data with local database

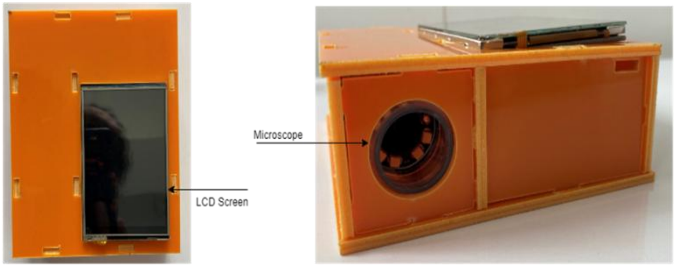

Fig. 6 The Prototype

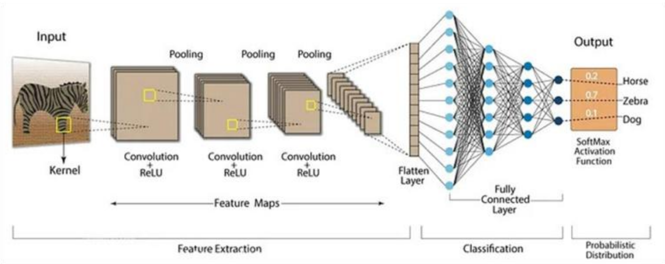

Fig. 7 CNN Model Architecture (Image Credit:https//what-is-convolutional-neural-network-cnn-deep-learning-b3921bdd82d5)

The confusion matrix that was generated by the model The model performs admirably for the bulk of the test cases, according to the confusion matrix. There are times when the model generates false positives and false negatives.

RESULTS

The CNN model excels at accurately identifying microplastics in images. It can successfully uncover intricate correlations and patterns between pixels that indicate the presence of microplastics and the type of polymer thanks to its convolutional layers. The knowledge of these visual patterns that the model has acquired allows it to correctly recognize microplastics in new, previously unknown photographs after sufficient training. This ability offers enormous promise for a range of applications, such as preserving the environment, ensuring industrial quality, and safeguarding aquatic ecosystems. With thorough training and optimization, the CNN model can perform and achieve astounding levels of accuracy, making it seem like a potent tool for identifying microplastics. The model's accuracy is 0.97%, and the F1 score is 1.0

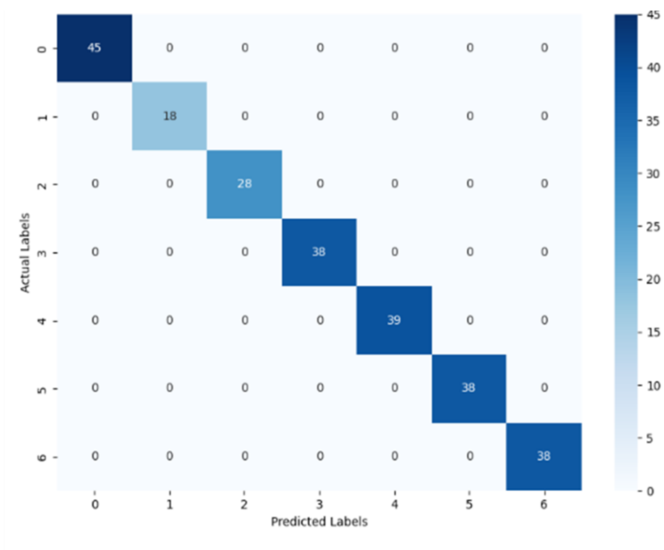

Fig 8 Confusion matrix showing the model's performance

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REFERENCES

[1]. O. Lai, “8 Shocking Plastic Pollution Statistics to Know About,” Earth.org - Past | Present | Future, Feb. 08, 2022. https://earth.org/plastic-pollution-statistics/

[2]. National Oceanic and Atmospheric Administration, “What are microplastics?,” Noaa.gov, Feb. 26, 2021. https://oceanservice.noaa.gov/facts/microplastics.html

[3]. K. Zhang et al., “Understanding plastic degradation and microplastic formation in the environment: A review,” Environmental Pollution, vol. 274, p. 116554, Apr. 2021, doi: https://doi.org/10.1016/j.envpol.2021.116554.

[4]. L. F. Amato-Lourenço, R. Carvalho-Oliveira, G. R. Júnior, L. dos Santos Galvão, R. A. Ando, and T. Mauad, “Presence of airborne microplastics in human lung tissue,” Journal of Hazardous Materials, vol. 416, p. 126124, Aug. 2021, doi: https://doi.org/10.1016/j.jhazmat.2021.126124.

[5]. Md. S. Bhuyan, “Effects of Microplastics on Fish and in Human Health,” Frontiers in Environmental Science, vol. 10, Mar. 2022, doi: https://doi.org/10.3389/fenvs.2022.827289.

[6]. P. A. Da Costa Filho et al., “Detection and characterization of small-sized microplastics (≥ 5 µm) in milk products,” Scientific Reports, vol. 11, no. 1, Dec. 2021, doi: https://doi.org/10.1038/s41598-021-03458-7.

[7]. A. Ragusa et al., “Plasticenta: First evidence of microplastics in human placenta,” Environment International, vol. 146, no. 106274, p. 106274, Jan. 2021, doi: https://doi.org/10.1016/j.envint.2020.106274.

[8]. D. Zhang et al., “Microplastic pollution in deep-sea sediments and organisms of the Western Pacific Ocean,” Environmental Pollution, vol. 259, p. 113948, Apr. 2020, doi: https://doi.org/10.1016/j.envpol.2020.113948.

[9]. B. Cocciaro, S. Merlino, M. Bianucci, C. Casani, and V. Palleschi, “Feasibility Study for the Development of a

Low-Cost, Compact, and Fast Sensor for the Detection and Classification of Microplastics in the Marine Environment," Sensors, vol. 23, no. 8, pp. 4097–4097, Apr. 2023, doi: https://doi.org/10.3390/s23084097.

[10]. J. Lin, H. Liu, and J. Zhang, "Recent advances in the application of machine learning methods to improve identification of the microplastics in environment," Chemosphere, vol. 307, p. 136092, Nov. 2022, doi: https://doi.org/10.1016/j.chemosphere.2022.136092.

[11]. M. Yurtsever and U. Yurtsever, "Use of a convolutional neural network for the classification of microbeads in urban wastewater," Chemosphere, vol. 216, pp. 271–280, Feb. 2019, doi: https://doi.org/10.1016/j.chemosphere.2018.10.084.

[12]. V. H. da Silva, F. Murphy, J. M. Amigo, C. Stedmon, and J. Strand, "Classification and Quantification of Microplastics (<100 μm) Using a Focal Plane Array–Fourier Transform Infrared Imaging System and Machine Learning," Analytical Chemistry, vol. 92, no. 20, pp. 13724–13733, Sep. 2020, doi: https://doi.org/10.1021/acs.analchem.0c01324.

[13]. Z. Chaczko, P. Wajs-Chaczko, D. Tien, and Y. Haidar, "Detection of Microplastics Using Machine Learning," IEEE Xplore, Jul. 01, 2019. https://ieeexplore.ieee.org/abstract/document/8949221 (accessed Jul. 21, 2020).

[14]. Y. Zhu, C. Hang Yeung, and E. Y. Lam, "Microplastic pollution monitoring with holographic classification and deep learning," Journal of Physics: Photonics, vol. 3, no. 2, p. 024013, Apr. 2021, doi: https://doi.org/10.1088/2515-7647/abf250.

[15]. Y. Zhu, C. Hang Yeung, and E. Y. Lam, "Digital holographic imaging and classification of microplastics using deep transfer learning," Applied Optics, vol. 60, no. 4, p. A38, Oct. 2020, doi: https://doi.org/10.1364/ao.403366.

[16]. O. Garcia-Garin et al., "Automatic detection and quantification of floating marine macro-litter in aerial images: Introducing a novel deep learning approach connected to a web application in R," Environmental Pollution, vol. 273, p. 116490, Mar. 2021, doi: https://doi.org/10.1016/j.envpol.2021.116490.

[17]. J. Wang et al., "Identification and detection of microplastic particles in marine environment by using improved faster R–CNN model," Journal of Environmental Management, vol. 345, pp. 118802–118802, Nov. 2023, doi: https://doi.org/10.1016/j.jenvman.2023.118802.

[18]. J. Lorenzo-Navarro et al., "SMACC: A System for Microplastics Automatic Counting and Classification," IEEE Access, vol. 8, pp. 25249–25261, 2020, doi: https://doi.org/10.1109/access.2020.2970498.

[19]. J. Lorenzo-Navarro et al., "Deep learning approach for automatic microplastics counting and classification," Science of The Total Environment, vol. 765, p. 142728, Apr. 2021, doi: https://doi.org/10.1016/j.scitotenv.2020.142728.

[20]. Z. Moorton, Z. Kurt, and W. L. Woo, "Is the use of deep learning an appropriate means to locate debris in the ocean without harming aquatic wildlife?," Marine Pollution Bulletin, vol. 181, p. 113853, Aug. 2022, doi: https://doi.org/10.1016/j.marpolbul.2022.113853.

[21]. J. Grant-Jacob et al., "Particle and salinity sensing for the marine environment via deep learning using a Raspberry Pi," Environmental research communications, vol. 1, no. 3, pp. 035001–035001, Apr. 2019, doi: https://doi.org/10.1088/2515-7620/ab14c9.

[22]. "Make Sense AI," www.makesense.ai. https://www.makesense.ai