Development of an Advanced AI Laboratory Module for Deployment on an Edge IoT Device for a Targeted Application: Microplastics Classification

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Abstract

Applying artificial intelligence (AI) to solve real-world problems requires students to understand and use AI tools in meaningful ways during their science, technology, engineering and math (STEM) education. Students must not only be able to use the tools but solve problems that might require training and testing appropriate AI models suitable for the application at hand. Students demonstrate that they are effective users of AI tools, including generative AI tools, for educational and learning purposes; however, developing and implementing AI solutions deployable for a specific problem on hardware represent unique technical skills valuable for the STEM workforce that would require integration of competencies from multiple fields.

In this paper, the development of a laboratory exercise for a technical elective course on Internet of Things (IoT) open to multiple engineering, engineering technology and computer science disciplines is described. The lab exercise is dedicated to training and testing a lightweight AI model to be implemented on an edge IoT device. This lab exercise is expected to significantly enhance AI learning and deployment skills of students working in multidisciplinary teams.

This lab presents a mechanism for image-based classification of microplastics, such as beads, nurdles, and small Styrofoam pieces, using a publicly available or student-acquired dataset. The exercise entails students learning how to train a lightweight machine learning model that is then deployed on a Raspberry Pi as edge IoT device to perform real time classification. Students then validate the model with data collected through a camera integrated with the Raspberry Pi.

The output of the AI model represents the type (label) of microplastics and results of analytics which are published to a Web-based dashboard. The dashboard provides educators and undergraduate students with visual feedback including component classification and performance metrics. The work not only presents AI and IoT on the edge but also establishes the lab framework for teaching embedded machine learning, edge computing, IoT and the cloud. The lab helps students learn core concepts, through hands-on project-based collaborative and engaged student learning that can then be applied to future projects or transferred to the workforce.

Targeted pedagogies include critical thinking for interpreting results of the AI solution that the students would train and test. Peer and collaborative learning are also utilized as the lab is conducted in teams. Constructivist teaching is employed through scaffolding exercises that form earlier labs, building knowledge and skills supporting this advanced lab.

Student learning is assessed by conceptual and reflective questions and prompts that require critical thinking from individual system outputs. The instructor can use student responses to evaluate student learning and the attainment of student outcomes, and reinforce concepts that are identified to need further discussion. Conceptual questions test students' knowledge base. Reflection questions assess their critical thinking and self-evaluation. The paper presents the developed lab exercise and sample scenarios with ranging difficulty of scene, followed by assessment questions to capture whether students have met relevant student learning outcomes. Other learning outcomes are assessed based on the technical performance of their work.

Introduction

Artificial intelligence (AI) has become an essential tool across many engineering disciplines, making the use of AI as well as the development of AI models among important skills for undergraduate students. Besides understanding AI concepts, ethical concerns related to AI, as well as the limitations of AI, engineering students must be exposed to hands-on experiences to train and/or implement AI models to solve real-world problems as part of their undergraduate engineering/computer science education. Although a significant number of students are familiar with using AI-powered tools, fewer students develop and implement solutions through hands-on exercises that allow training and critically evaluating AI models based on the real datasets in a classroom environment.

In this paper we present a hands-on laboratory framework to develop STEM students' skills in AI model implementation, training, evaluation, and application through hands-on exercises by using previously-acquired images and existing microplastics datasets [1]. The advanced laboratory exercise provides sufficient detail to allow ease of use, and clarity of the used AI models and solutions, while allowing students to gain hands-on experience with AI and learn how to analyze model performance in an applied domain. This work is in response to the following two research questions:

(a) Can transfer of learning be successfully achieved in remote hands-on engaged student learning (ESL) scenarios?
(b) How well do online tutorials contribute to hands-on ESL, when coupled with physical hardware accessible at home?

Previous results have shown that (a) transfer of learning can successfully be achieved in remote hands-on engaged student learning environments for the majority of students [2]; and (b) online tutorials contribute positively to hands on ESL when coupled with physical hardware for most students [2]. This exercise is prepared with these findings in mind.

The laboratory is incorporated in the context of an ENGR 4351 - Internet of Things (IoT): Devices and Communication course at Texas A&M University-Corpus Christi where sensors, microcontrollers and other edge devices are connected to cloud services to receive, display and process multi-sensor data for a given problem for a real-time solution [2]. The students are lent the devices and can take them home. This laboratory can also be implemented in the ENGR 4352 – Artificial Intelligence (AI) in Engineering and Science Applications course to offer students hardware/software interfacing experience with trainable AI. The IoT course utilizes KeySight IoT development kits (U3813A) which incorporate BeagleBone Green as a microcontroller on a development board with built-in sensors, XBee communication devices, as well as additional cloud interfacing components and capabilities [3]. The project team previously developed laboratory exercises to accompany the development kit's use to meet the learning objectives of the course [4]. To increase accessibility, additional laboratory exercises were developed using Raspberry Pi platform to serve undergraduate researchers' learning as well as laboratory teaching with hardware [2] that uses scaffolding to train students on the use and integration of different components throughout the laboratory exercises. The last laboratory exercise implemented a pre-trained AI model onto a Raspberry Pi system whose application was demonstrated on plastic debris detection [5].

The laboratory exercise presented here builds on the experiences with Raspberry Pi, and adds on the AI model that is trained off board, validated and tested by the students, as opposed to being pre-trained. This opportunity to train the AI model based on their targeted dataset adds an advanced capability to the students' AI-based solution development skillset.

The rest of this paper covers background on relevant work and learning pedagogies, followed by description of the labs and methods used. Results from different detection scenarios are presented at the end, together with sample conceptual and reflective questions for students to assess their learning and attainment of learning outcomes via critical evaluation of lab results. Conclusions summarize the project, implemented pedagogies, and their connection to student learning.

Background

Related Work

Recent literature suggests an increasing interest in implementing artificial intelligence related concepts into the engineering curriculum in more interactive and efficient ways: According to the systematic review by Jacobs *et al.* [6], the use of AI tools to facilitate a personalized learning experience, interactive problem solving, and student support in engineering education is rising. The authors warn against the problems of unplanned AI implementation that may result in issues related to academic honesty, ethics concerns, and over-dependence on automated technologies. Similarly, Liu *et al.* state that the growth of AI-based tools, like virtual laboratories, bring along challenges such as data privacy [7].

A number of studies emphasize how crucial project-based and hands-on education are when implementing emerging technologies [2], [8]. According to Hallmark *et al.*, who summarize the results of recent studies, AI-supported instruction works best when it is integrated into structured learning environments that follow standard learning theory [8]. Additionally, McLauchlan *et al.* present complementary evidence that students place a high value on guided tutorials, demonstrations, and practical laboratory exercises when learning new technical concepts [4]. Structured hands-on learning experiences are, therefore, well accepted as part of effective learning pedagogies and their educational significance.

The importance of introducing students to comprehensive AI workflows is also demonstrated by research on the application of AI in education [6], [9]. Both Jacobs's [6] and Sakib's [9] group's research studies point out that although AI tools can increase productivity and conceptual understanding, students gain the most when they actively participate in hands-on learning. These research findings suggest that over-reliance on pre-trained systems may restrict opportunities for skills development and critical thinking.

Effective techniques for providing practical engineering education have been extensively covered in the literature, including remote and cloud-based learning environments [10], [11]. McLauchlan *et al.* and Mehrubeoglu *et al.* show that well-planned remote lab exercises that allow flexible access to hardware can offer significant practical experiences compared to conventional labs only conducted as in-person labs [4], [10], [11]. Similarly, Cecere *et al.* demonstrate how project-based courses with flexible or remote infrastructure can effectively involve students in challenging, interdisciplinary problem-solving skills and learning [12]. The use of cloud-based platforms to improve accessibility and reproducibility in AI-focused educational modules is supported by these findings.

Previously, incorporation of machine learning and visual data in engineering learning environments had been investigated [13] with an application of plastic debris detection [5]. Hicks *et al.* show how students can be introduced to machine learning ideas through practical, hands-on exercises using images captured by a microcontroller and an external camera [13]. Instead of depending only on pre-built models, the authors emphasize the importance of helping students through data processing, analysis, and evaluation. This approach is in line with the learning outcomes of laboratory exercises where students may use real and meaningful datasets to comprehend AI behavior, performance indicators, and constraints through analysis and critical thinking.

When combined, these findings indicate that practical, project-based, repeatable learning environments that emphasize full AI workflows are beneficial for and effective in engineering AI education. There are gaps yet to be filled to create educational modules that specifically concentrate on AI model training, evaluation, and inference using real-world environmental data or images, even though previous research has shown the benefits of AI tools, remote labs, and experiential learning. By providing a cloud-based, organized method focused on microplastic detection, the laboratory architecture described in this research expands upon these educational underpinnings, providing a new learning platform in line with modern technologies.

Other pedagogical methods incorporated include peer and collaborative learning (CL), as the lab is conducted in teams. Collaborative learning examples in literature cover Roney's use of CL methods to teach students about energy systems [15]. In addition, Pool *et al.* utilize CL methods as a framework to facilitate students working on creating new lab modules [15]. Student experience with skills learned through hands-on project-based collaborative and engaged student learning can then be applied to future projects as also intended for the lab presented in this paper.

Applied Learning Pedagogies

Students often have limited practical understanding of the evaluation of AI model training and how to use AI model training for real world problems. The advanced laboratory exercise presented here incorporates constructivism pedagogical concepts where students learn to use advanced software and hardware tools through scaffolding exercises throughout the semester, building on their prior knowledge. Constructivism learning theory is defined as "active construction of new knowledge, based on learner's prior experience" [16], [17]. These exercises introduce the students to the concepts step by step, building on previous knowledge and expanding that knowledge over time. Adding the project-based learning component to scaffolding [18], the students are introduced to a relatable problem (microplastics detection and identification / classification), for which they need to develop an AI solution. This relatable problem allows the students to remain engaged in the exercise. Project-based learning is particularly important as project-based problems possess multiple and complex solutions that require the use of synthesized knowledge from a variety of courses and disciplines [19]-[21]. In the presented context, hands-on engaged student learning occurs through hardware that is provided to the students where the students not only have to develop and test their AI models but also implement them in hardware related to edge IoT devices for real-time testing.

Advanced Laboratory Exercise for AI Model Development and Implementation

The activity described here is designed for upper division undergraduate STEM students to introduce them to artificial intelligence and data-driven approaches beyond the use of pretrained

AI models [22]. The activity specifically targets undergraduate engineering students, regardless of their technical skills, to help them learn how to train AI models by providing these students with annotated datasets and guided instructions for implementation. The module can be applied to courses in engineering, computer science, data science, and in general technical electives that introduce the concepts of machine learning.

The implementation of the first part of the laboratory exercises that involve AI model development through online cloud-based tools helps to reduce hardware and software barriers through the use of Google Colab [23] and open-source software. Google Colab enables experimentation through Google's cloud servers. This approach allows instructors to implement the laboratory in either the traditional format, or both the hybrid and fully remote course format, resulting in a flexible instructional environment.

Learning Objectives

The learning objectives for this laboratory include the following: by the end of this exercise the students will

1. **become familiar with the basics of object detection in images,** such as bounding boxes, class labels, and confidence scores,
2. **implement a problem-based AI solution** using a suitable deep learning model to identify objects,
3. **train an AI model using annotated image datasets**,
4. **evaluate the performance of the trained AI model** using confusion matrices, and precision, recall, and accuracy metrics,
5. **incorporate cloud-based computing platform** into the IoT-based hardware implementation, and
6. **implement AI in a domain-specific problem** (in this case, microplastics detection/identification) to learn how AI can be applied for specific problems.

The developed laboratory module focuses on familiarizing the students with artificial intelligence concepts by detecting objects (microplastics) in images. This particular lab aims to train, test, and evaluate a lightweight deep learning model on microplastics images that can then be deployed on hardware, to provide students with the opportunity to experience the AI model training, testing and evaluation process in a classroom setting with a meaningful relatable problem, followed by hardware interfacing for real-time classification. This lab covers the student learning outcomes at different stages of the exercise while incorporating different learning pedagogies.

As mentioned earlier, the laboratory exercise is designed for the AI module to be trained and tested in a cloud-based system called Google Colab which provides a flexible platform for AI model training, testing and deployment through cloud services. The chosen example application of microplastics detection is a relatable problem for students. Microplastics dataset utilized in the AI training exercise is in YOLO format and already labeled. Students are instructed to train, validate, and test models using a YOLOv8n model-based object detection framework. The main goal of this part of the lab is to properly train the chosen AI model using existing real-world datasets to create an effective AI model for the purposes of the adopted problem (microplastics detection and identification). The students must learn the necessary concepts and tools through project-based learning in collaborative learning environments.

After successful quantitative assessment of the trained AI model, the laboratory exercise guides the students to use the trained model to perform AI inference on previously unseen images to detect objects with bounding boxes and confidence scores. These results can then be used by the students to comment on the accuracy and prediction capability of the model. The workflow generates structured results, such as annotated images, detection summary and model performance graphs, which enable students to test and analyze model behavior, and experience a real-world application from dataset acquisition to model training and testing to develop their theoretical and algorithmic foundations before deploying the working AI model on hardware. The students employ scaffolded conceptual learning and critical thinking skills to accomplish the tasks associated with model quality assessment and suggest performance related improvements.

Instructional Methodology

From a technical standpoint, the laboratory exercise presents students with applied artificial intelligence concepts in a systematic and approachable workflow that is deployable on IoT devices (Fig. 1). The hands-on practical application aspect is focused on data access, model training, evaluation and interpretation with a relatable real-world problem (microplastics detection, identification and classification) as opposed to the technical complexity of the algorithm. Here, the educational goal is the effective use of the tools and techniques with critical thinking and applied creative solutions to improve performance. The AI model is developed on the Google Colab platform, giving students access to computational capabilities via the cloud, including GPU, without the need to install software locally. This platform removes multiple technical barriers that could otherwise be time consuming for students to resolve and discouraging at the same time. Instead, the focus is turned on the deployment of the AI solution in in-person, hybrid, and remote learning environments.

Students make use of a pre-structured dataset of microplastic images that has been processed and organized into an object-detection format and subsets (training, validation, and testing). It is based on an existing dataset structure that exposes the students to the real conditions of data that reinforces the concept of reproducibility and data organization. In addition, it is a quicker way to access data to get them started and excited about this project. An object detection model is applied to ensure that the training and inference objective can be accomplished within regular laboratory time requirements. The operations of training, evaluation, and inference are seen as a unified workflow where students explore metrics of performance, visualize the outputs of detection, and analyze the confidence score and processing time. These results lay the foundation for students on which to improve their analysis skills while learning the implementation of AI models. Figure 1 summarizes the technical tasks the students must accomplish to develop and deploy their AI solution.

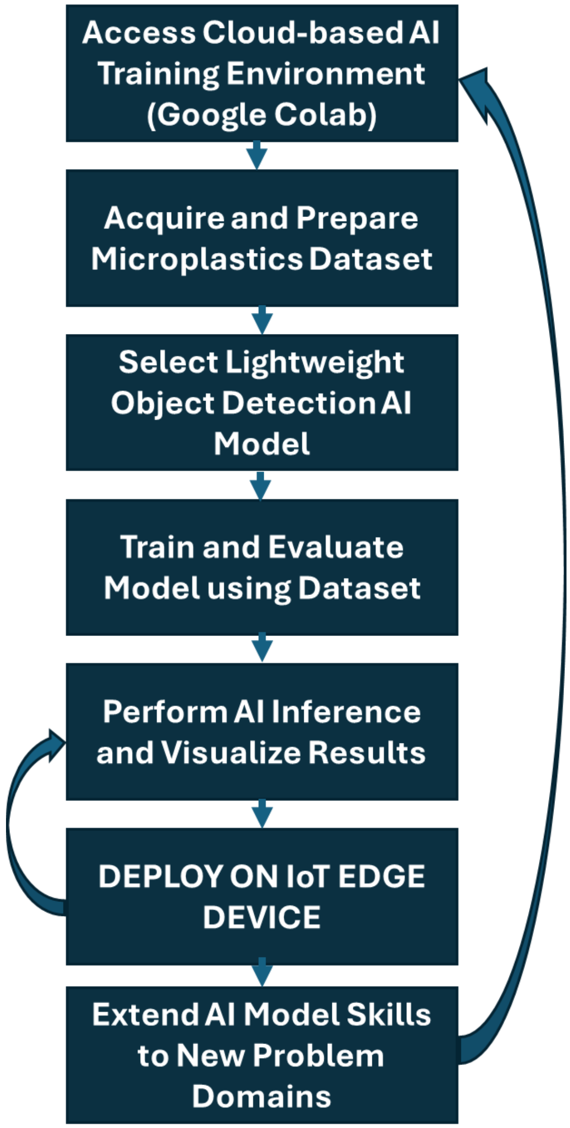

Figure 1. Instructional workflow for training, evaluating, and applying an AI-based microplastics detection model in a cloud-based learning environment.

Results

Technical Project Outcomes

Figures 2-11 show results for different scenarios of plastics detection, from a relatively simple case of three samples of a single object type (Styrofoam beads) to multiple objects of the same type, as well as multiple multicolored plastic samples. Together with the performance metrics produced, the students are able to analyze, interpret, and make recommendations for improvement of the designed and deployed AI model for a given application using prior knowledge that they build throughout the course, critical thinking and analysis skills.

Scenario I: Simple Case – Single Class, Single Color, Single Size, Few Samples

The following scenario (Fig. 2) represents a simple case where the scene only shows a single class (Styrofoam beads) with only few samples in the scene. Figure 3 shows the highest average confidence scores for classification in this simple scenario, where the students must explain.

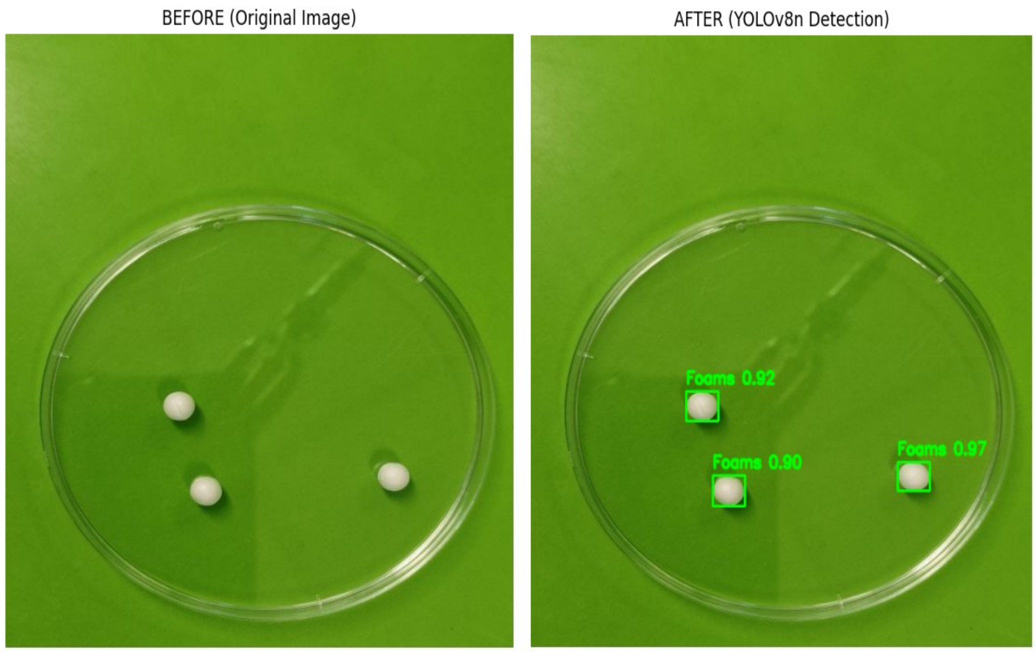

Figure 2. Detection and classification results using bounding boxes for a simple case of three objects of the same type and size, in the presence of shadows.

	Metric	Value
0	Model	YOLOv8n (best.pt)
1	Total Detections	3
2	Beads Count	0
3	Foams Count	3
4	Avg Confidence	0.9274
5	Max Confidence	0.9651
6	Min Confidence	0.8999
7	Preprocess Time (ms)	2.84
8	Inference Time (ms)	7.55
9	Postprocess Time (ms)	1.23
10	Total Time (ms)	11.62

Figure 3. Performance metrics produced through YOLOv8n for detection and classification of image in Figure 2.

Scenario II: Simple Case – Single Class, Single Color, Single Size, Many Samples

Figure 4 represents a more complex scenario where the scene still only shows a single class (Styrofoam beads) but this time many more samples are visible. Figure 5 summarizes the performance metrics. The students must conduct comparative analysis among different scenarios.

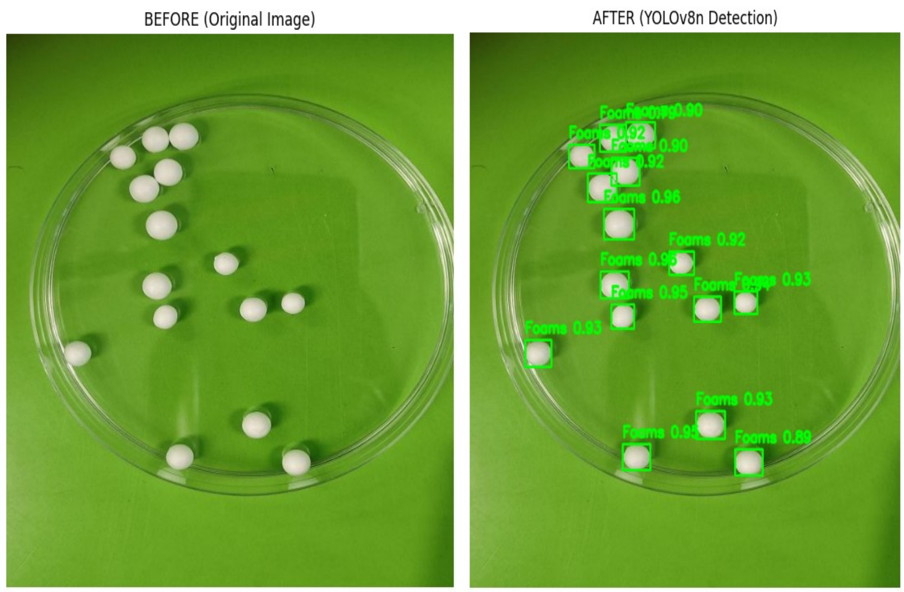

Figure 4. Detection and classification results in the case of single object type with 15 samples, with bounding boxes and confidence scores, using YOLOv8n

	Metric	Value
0	Model	YOLOv8n (best.pt)
1	Total Detections	15
2	Beads Count	0
3	Foams Count	15
4	Avg Confidence	0.9191
5	Max Confidence	0.9561
6	Min Confidence	0.7912
7	Preprocess Time (ms)	1.90
8	Inference Time (ms)	8.40
9	Postprocess Time (ms)	1.29
10	Total Time (ms)	11.58

Figure 5. Performance metrics produced through YOLOv8n for detection and classification of images in Figure 4.

Scenario III: Medium Complexity Case – Multiple Classes, Multiple Colors, Multiple Sizes, Few Samples

Figure 6 represents a scenario of medium complexity where the scene shows multiple classes (plastic beads and Styrofoam beads) with only 12 samples. We note that the samples are well separated, with several samples clustered along the edge resulting in lower confidence scores in class identification (Fig. 7). Students are prompted to pay attention to these details in their interpretation of performance metrics results.

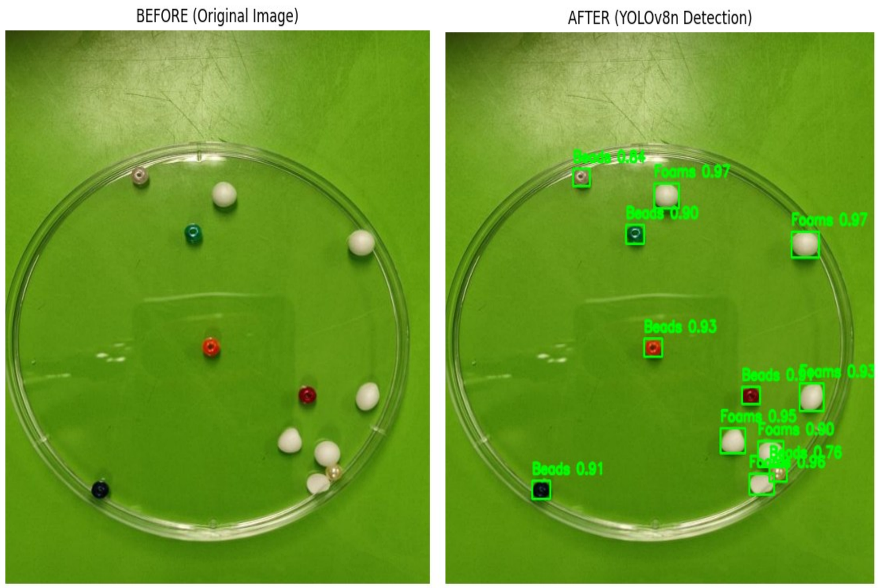

Figure 6. Detection and classification results in the case of multiple object types with bounding boxes and confidence scores for 12 samples (medium complexity) using YOLOv8n.

	Metric	Value
0	Model	YOLOv8n (best.pt)
1	Total Detections	12
2	Beads Count	6
3	Foams Count	6
4	Avg Confidence	0.9101
5	Max Confidence	0.9699
6	Min Confidence	0.7614
7	Preprocess Time (ms)	2.00
8	Inference Time (ms)	8.20
9	Postprocess Time (ms)	1.28
10	Total Time (ms)	11.48

Figure 7. Performance metrics results produced through YOLOv8n for detection and classification of objects shown in images in Figure 6.

Scenario IV: Medium Complexity Case – Multiple Classes, Multiple Colors, Multiple Sizes, Few Samples

Figure 8 represents a medium complexity case with multiple classes (plastic and Styrofoam beads) with 12 samples. Compared to Scenario III above, many more samples are visible along the edges of the dish, which could potentially “confuse” the algorithm. The samples are generally well separated, with smaller beads resulting in lower classification confidence scores than larger beads, and samples near edges resulting in lower confidence scores. Clustered samples are generally identified with the lowest confidence scores. Figure 9 shows the performance results.

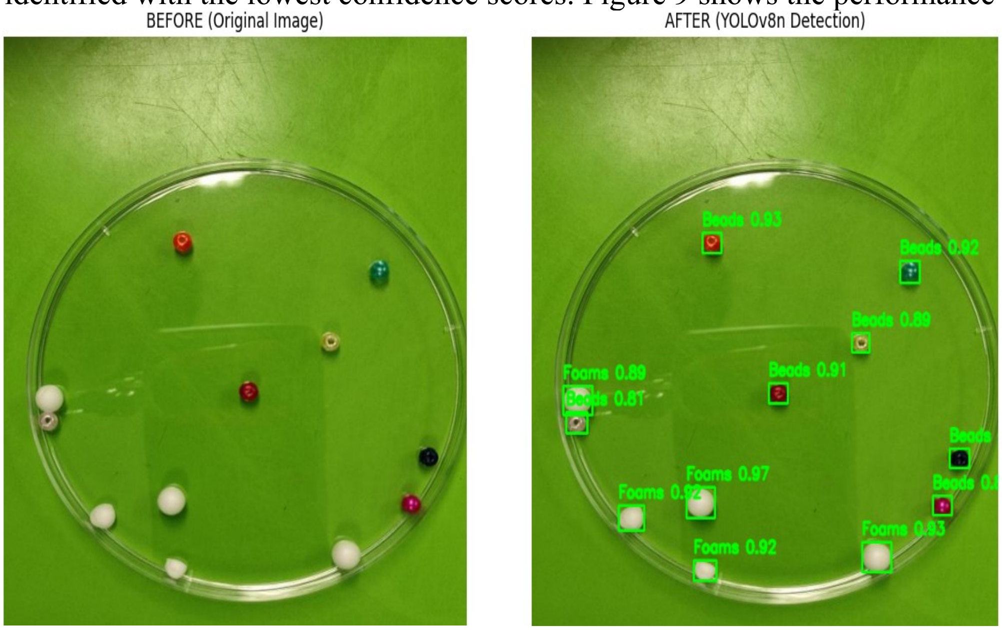

Figure 8. Implementing YOLOv8n for microplastics detection and classification with mixed objects of different sizes and colors (medium complexity case).

	Metric	Value
0	Model	YOLOv8n (best.pt)
1	Total Detections	12
2	Beads Count	7
3	Foams Count	5
4	Avg Confidence	0.9070
5	Max Confidence	0.9655
6	Min Confidence	0.8108
7	Preprocess Time (ms)	2.47
8	Inference Time (ms)	10.94
9	Postprocess Time (ms)	2.40
10	Total Time (ms)	15.81

Figure 9. Performance metrics produced through YOLOv8n for images in Figure 8.

Scenario V: High Complexity Case – Multiple Classes, Multiple Colors, Multiple Sizes, Many Samples

Figure 10 represents a scenario of high complexity where the scene shows multiple classes (plastic and Styrofoam beads) with 19 samples. The samples are generally well separated; however, many occur around the edges of the dish, with some showing reflections. Due to the number of samples in the scene, this case displays the lowest average confidence scores for identification (Fig. 11).

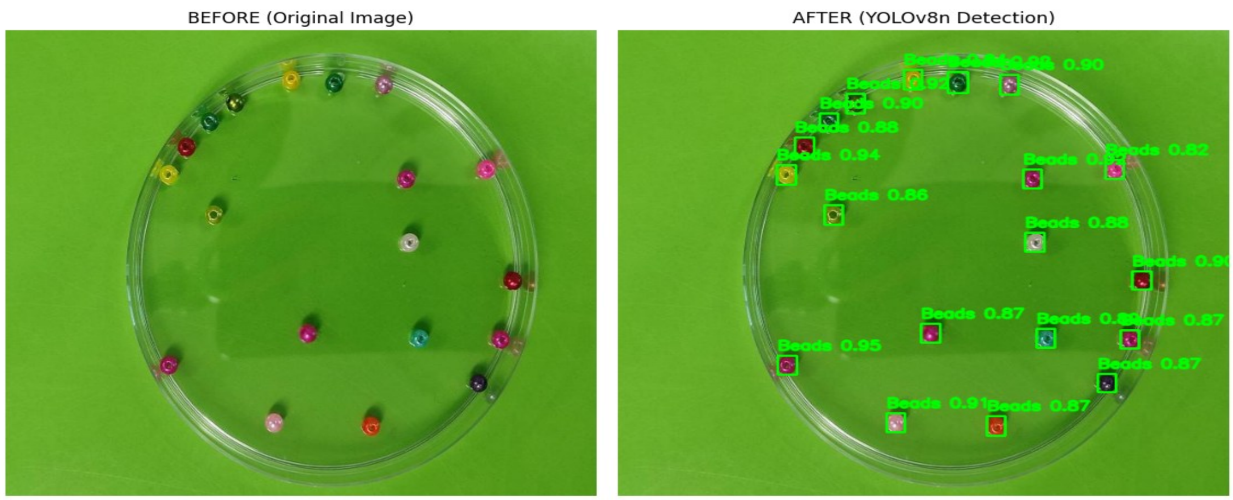

Figure 10. YOLOv8n detection and identification results with confidence scores for mixed color microplastic samples.

	Metric	Value
0	Model	YOLOv8n (best.pt)
1	Total Detections	19
2	Beads Count	19
3	Foams Count	0
4	Avg Confidence	0.8959
5	Max Confidence	0.9537
6	Min Confidence	0.8245
7	Preprocess Time (ms)	1.90
8	Inference Time (ms)	8.60
9	Postprocess Time (ms)	1.43
10	Total Time (ms)	11.93

Figure 11. Performance metrics produced through YOLOv8n for detection and classification of objects in the image of Figure 10.

These results help students visualize the effectiveness of the algorithms they developed based on the complexity of the analyzed scene. The students have an opportunity to evaluate the results based on different scenarios including simple cases (single object type, few objects in the scene, well separated samples) to more complex cases (large number of objects with different colors and/or sizes, clustered or on edges with reflections). As can be seen progressively from Figures 2 to 11, as the scene becomes more complex, the average confidence score for detection and identification goes down.

Student Learning and Assessment

The following conceptual and reflective questions are formulated to assess students' conceptual learning and critical thinking that connect the student learning outcomes to the described exercise and activities. The students base their responses on the AI models they create and results they obtain:

1. For how many classes of microplastics was your model trained?
2. What do the confidence scores show in the scenarios above?
3. Identify at least three reasons why confidence scores varied in the classification results from different scenarios.
4. Provide three ways to improve classification results and confidence scores?
5. Comment on the attributes of microplastics (size, shape, color, orientation, location, etc.) that impact classification results and confidence scores. Can you think of other reasons why the classifier may not be as effective in performing classification (hint: environmental factors)
6. How can the trained AI model be improved and extended to successfully identify other types of microplastics?
7. What are some of the challenges you foresee with IoT-deployed edge devices in the environment for detecting and classifying microplastics *in situ*?
8. What are the limitations of your algorithm?
9. How has this project-based learning (PBL) assignment improved your understanding of AI and IoT?
10. What challenges did you encounter when deploying the AI model onto IoT hardware? How did you resolve the issues?
11. What technical aspects from the application can you leverage for use in your other engineering course projects, such as capstone design project?
12. Did you find the laboratory tutorials provided and available online in Canvas useful in your learning? Please explain your response.
13. Were you able to use knowledge and skills acquired in previous labs (transfer of learning) to complete this lab both in class and remotely?

Deployment on IoT Devices

YOLOv8n is a light-weight AI model that can be implemented in IoT related edge devices, such as Raspberry Pi. Once finalized, the trained AI model can be deployed on the Raspberry Pi 4 or 5 for real-time detection and classification of new scenes or images, and is part of the advanced lab. The focus of this paper has been on developing an AI model that is trained and tested by students that can then be implemented on hardware. The AI model is chosen to be suitable for low-resource IoT edge devices without requiring complex hardware and systems.

Conclusion

The paper presents a cloud-based instructional laboratory aimed at assisting STEM, and in particular engineering, engineering technology and computer science students to acquire practice-based skills in the application of AI to a real-life engineering, in this case environmental, domain problem. The module also focuses on the entire AI workflow by instructing students on dataset preparation, training, evaluation, and AI inference or prediction of objects within microplastics images. Google Colab and an object detection model allow the laboratory to be reproducible and accessible both in remote and in-person classroom settings. The students are trained to extract and visualize the results to perform effective performance evaluation of their model, and use critical thinking to provide meaningful feedback on how the results can be improved. The exercise engages students to think critically and analytically to understand the performance results and how performance is impacted with the scene complexity and objects under consideration for detection and classification. The students interpret key inference parameters, including object counts by class, confidence scores (minimum, maximum, and average). In addition, they have an opportunity to interpret processing times for preprocessing, inference, postprocessing, as well as the total execution time.

This laboratory exercise shows the implementation of AI concepts in engineering education using a hands-on, data-driven approach where students learn and practice to train AI models for specific problems, in this case microplastics detection and classification, in project-based learning. Students are able to see, firsthand, the limitations of AI, performance challenges in complex scenes and scenarios, and aspects of AI as they visualize the results of their own AI solution. The conceptual and reflective questions at the end guide the students to connect theoretical aspects of student learning outcomes to the necessary skills and performance to meet the learning outcomes of the lab. This lab can be extended to other applications and domains to create AI solutions targeting similar learning goals. The lab is created with IoT and edge devices in mind such that the developed models are implementable on edge devices to allow software/hardware integration for specific and portable solutions in real-time applications.

Acknowledgment

This project is supported in part by grant #2044255 from the U.S. National Science Foundation.

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