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BOARD #130: AI-Driven Mussel Behavior Monitoring Using An Accessible 3D Imaging System

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AI-Driven Mussel Visual Monitoring: An Accessible 3D Imaging System

Abstract

Freshwater mussels are essential parts of our ecosystems to reduce water pollution. As natural bio-filters, they deactivate pollutants such as heavy metals, providing a sustainable method for water decontamination. This project will enable the use of Artificial Intelligence (AI) to monitor mussel behavior, particularly their gaping activity, to use them as bio-indicators for early detection of water contamination. In this paper, we employ advanced 3D reconstruction techniques to create detailed models of mussels to improve the accuracy of AI-based analysis. Specifically, we use a state-of-the-art 3D reconstruction tool, Neural Radiance Fields (NeRF), to create 3D models of mussel valve configurations and behavioral patterns. NeRF enables 3D reconstruction of scenes and objects from a sparse set of 2D images. To capture these images, we developed a data collection system capable of imaging mussels from multiple viewpoints. The system featured a turntable made of foam board with markers around the edges and a designated space in the center for mounting the mussels. The turntable was attached to a servo motor controlled by an ESP32 microcontroller. It rotated in a few degree increments, with the ESP32 camera capturing an image at each step. The images, along with degree information and timestamps, are stored on a Secure Digital (SD) memory card. Several components, such as the camera holder and turntable base, are 3D printed. These images are used to train a NeRF model using the Python-based Nerfstudio framework, and the resulting 3D models were viewed via the Nerfstudio API. The setup was designed to be user-friendly, making it easy for educational outreach engagements and to involve secondary education by replicating and operating 3D reconstructions of their chosen objects. We validated the accessibility and the impact of this platform in a STEM education summer program. A team of high school students from the Juntos Summer Academy at NC State University worked on this platform, gaining hands-on experience in embedded hardware development, basic machine learning principles, and 3D reconstruction from 2D images. We also report on their feedback on the activity.

Index Terms

Mussels, Neural Radiance Fields (NeRF), ESP32, NerfStudio API, 3D Design.

I. Introduction

Mussels play a critical role in maintaining the health of aquatic ecosystems by serving as natural biofilters. Their feeding behavior involves filtering large volumes of water, allowing them to absorb and trap various pollutants, including heavy metals and other harmful substances. This filtration process not only helps reduce pollution but also improves the clarity of the water, making mussels invaluable for mitigating water contamination in our freshwater systems. As such, mussels have become essential in environmental monitoring, acting as bioindicators of ecosystem health. Their ability to filter and accumulate pollutants makes them ideal subjects for studying the effects of pollution on aquatic environments and for identifying areas in need of water quality intervention[25], [21], [6], [42]. By monitoring mussel behavior, particularly gaping activity, it may be possible to gain insight into environmental stressors and pollutant levels in the water, providing an effective and sustainable method for water quality assessment.

Freshwater mussels are considered one of the most reliable bioindicators of water quality thanks to their sensitivity to environmental changes. As filter feeders, they respond quickly to fluctuations in water quality by altering their physiological behavior, particularly their gaping patterns. When exposed to pollutants such as heavy metals, observable changes in mussels' gaping activity make these excellent indicators of the presence of contaminants[41], [9]. These behavioral changes potentially may provide valuable data that can be used to assess levels of pollutants in water bodies, enabling early detection of contamination before it affects larger ecosystems[16], [43].

Our long-term goal is to produce an imaging system capable of visually tracking the configuration of mussels underwater in natural settings. These initial efforts have focused on developing the imaging system in controlled settings such as fish tanks and waterbeds. For this purpose, we developed a 3D imaging system for mussels in dry environments first. These 3D models are intended to aid in the estimation of the mussel's configuration once they are underwater. This is to help build a dataset that can be used for training AI-based recognition models. The system proposed in this article enables the generation of photorealistic 3D models using an commercially available ESP32 camera connected microcontroller developed by Espressif [11] and a rotating stage. We made use of state-of-the-art 3D reconstruction tools known as Neural Radiance Fields (NeRF) [26] to build the models. Fig. 1 provides an overview of our system components and the preliminary outcomes from the photorealistic 3D model.

We worked on making this platform accessible to STEM enthusiasts and the K-12 community in particular by making it affordable, reproducible and easy to use. For this purpose, we partnered with the Juntos program [4] at NC State University to validate the accessibility of our platform and disseminate our work. Juntos, meaning "together" in Spanish, is a program that works to unite community partners to provide Latino students in grades 8-12 and their parents with knowledge, skills, and resources to ensure high school graduation and broaden post-secondary career and academic opportunities. The Program

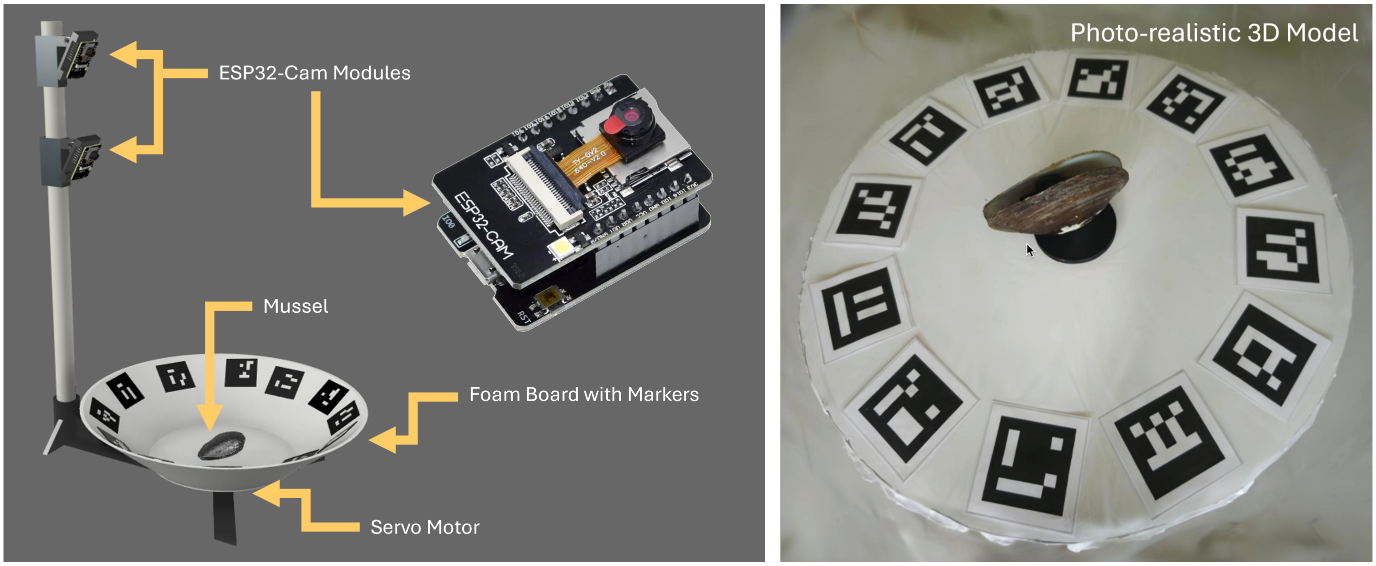

Fig. 1. Diagram of our system [left] and illustration of the output from the photorealistic 3D model [right].

does this through family engagement events, including a workshop curriculum, Juntos 4-H Clubs for youth, academic success coaching with a coordinator, and summer programming opportunities. The multifaceted partnerships between NC State Extension's 4-H and Family and Consumer Sciences (FCS) Program agents, school and university administrators and staff, higher education institutions, and community volunteers make the Juntos Program a sustainable success in many communities across the United States.

In section II, we provide an overview of our efforts on mussel monitoring and other imaging systems in this outreach context. Section III describes the hardware system for image acquisition, and section IV provides details of the software pipeline for 3D reconstruction. Section V reports on the results of our educational deployment with Juntos, and section VI concludes our article and provides some future directions.

II. Related Work

Early research on mussel behavior tracking primarily utilized Hall-effect sensors, inertial sensors, and visual sensors, each with distinct advantages and limitations in capturing mussel responses to environmental factors. Hall-effect sensors, which detect changes in gape behavior by measuring the movement of a magnet placed on one valve through sensing magnetic field, have been commonly employed in both laboratory and field settings [27], [1], [29], [7]. These sensors have proven effective in monitoring mussel responses to stressors such as turbidity and contaminants, with species-specific differences observed in gape responses [14], [22], [33], such as *Corbicula fluminea* closing its shells more readily than *Lampsilis radiata* in high-turbidity conditions [8], [34]. However, Hall-effect sensors often require mussels to be fixed to pedestals, limiting their natural movement and reducing the ecological relevance of the data. To address this limitation, inertial sensors, such as accelerometers, have been introduced [2], [30]. These sensors allow mussels to move freely on the substrate, providing more realistic behavioral data by tracking horizontal movement and continuously monitoring valve gape activity. While accelerometers offer significant advantages in capturing natural behaviors, they present challenges in terms of power consumption and the complexity of data interpretation. In addition to Hall-effect and inertial sensors, visual sensors have been explored as a noninvasive alternative for tracking mussel behavior. These systems use cameras combined with machine learning algorithms to monitor shell movements in real time, offering high spatial resolution and the ability to observe mussels in complex natural environments. For example, the MarineCanary project has demonstrated the potential of visual sensors for monitoring water quality by tracking mussel behavior as a bioindicator of contaminants [19]. However, visual sensors come with their own set of challenges, including high data processing demands and difficulties in differentiating mussels from other objects in the environment. Despite these limitations, visual sensors offer valuable advantages in terms of flexibility and resolution, which, when combined with Hall-effect and inertial sensors, could provide a more comprehensive and accurate system for monitoring mussel behavior in situ. Table I outlines key methods, their advantages, and limitations. In summary, while Hall-effect and inertial sensors have been effective in studying specific mussel behaviors, visual sensors offer enhanced spatial resolution and flexibility, although they introduce increased data complexity [15], [10], [5].

Thanks in part to the recent developments on embedded devices and 3D printing, reproducible imaging platforms have become more accessible to all levels of education as well as citizen scientists. For example, the MicroscPy [40] project provides an entire microscope built using LEGO bricks and 3D printed components. This platform is powered by Raspberry

TABLE I
COMPARISON OF DIFFERENT TRADITIONAL MUSSEL MONITORING METHODS.

Method	Key Techniques Used	Advantages	Limitations
Hall-Effect Sensors	Magnetic field detection	Effective for tracking valve gape (turbidity)	Restricts natural movement
Inertial Sensors	Acceleration measurement	Tracking horizontal movements with gape	Power consumption, calibration issues
Visual Sensors (Marine Canary)	Camera system, ML-based algorithms	Visual real-time monitoring	Mussels are fixed in these setups
Multi-modal Systems	Integration of different sensor data streams	Addresses limitations of individual approaches	Increased complexity in setup and analysis

Pi and Arduino microcontrollers. The Matchboxscope [24] introduces a low-cost incubator-contained microscope powered by an ESP32 microcontroller. One of the advantages of this platform is its low-cost, which is one order of magnitude lower when compared to a Raspberry Pi setup. Another platform is Forabot [31], an accessible robotic system for the imaging and sorting of microscopy fossils. In this article, we present a platform that takes advantage of these recent trends by producing an affordable, reproducible, and easy-to-use 3D imaging system.

III. EMBEDDED DESIGN

For the implementation of the mussel imaging system, an ESP32-CAM module was mounted on a servo-motor platform. The ESP32-CAM is a compact camera module that features the ESP32-S chip, priced at approximately $10. It includes an OV2640 camera, several GPIOs for connecting peripherals, a microSD card slot for storing captured images or files, and Wi-Fi functionality for transmitting images to cloud storage. The servo motor, MG90S, provides a torque of 2.2 kg/cm. In other words, it can lift a weight of 2.2 kg suspended 1 cm from its axis. The servo motor operates within a voltage range of 4.8V to 6.5V.

A custom-designed tunable platform was fabricated using foam markers around the edges, with designated spaces in the center for positioning. Additionally, several 3D-printed components were utilized to secure the cameras and serve as the base for the foam structure that is connected to the motor. Fig. 2 illustrates the main 3D designed components, and Fig. 1 shows the entire system. The upper and lower cameras are connected via digital ports to enable serial communication. The lower camera acts as the master by controlling the servo motor and sending commands to trigger the upper camera. The design files and assembly instructions can be found online at https://github.com/ARoS-NCSU/Mussel-3DImager/.

Image capture proceeds by having the lower camera (the master) rotate the servo by a small amount (e.g., 10 degrees), having both cameras capture images, and using the current timestamps and rotational angles as part of the file names. Once the imaging is complete (i.e., there has been a full 360 degrees of rotation), the images are sent to a Google Drive folder via Wi-Fi, making the data accessible for 3D reconstruction.

IV. 3D RECONSTRUCTION

A. Neural Radiance Field (NeRF) Methodology

Neural Radiance Fields (NeRFs) are one of the most prominent neural field architectures [44], which are used as the state-of-the-art in 3D reconstruction and view synthesis from 2D images [26]. It is a neural network based approach that learns to represent a scene's volumetric density and view-dependent emitted radiance, allowing us to generate new images from angles not seen in the training set. The process requires a set of 2D images that observe the same static scene as input. The structure

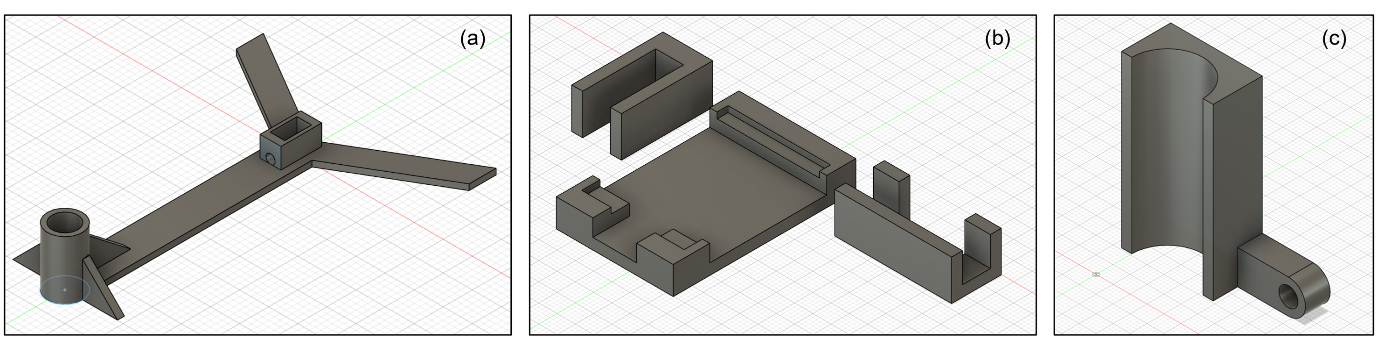

Fig. 2. Main 3D Components Designed: (a) The base has a housing for the servo as well as for the PCB tower holding the ESP32-CAM modules. (b) The camera mount includes some clips to hold the module in place. (c) The PCB adapter is used to attach the camera mount to the PCB and to allow it to be tilted. The scale is not the same between the components.

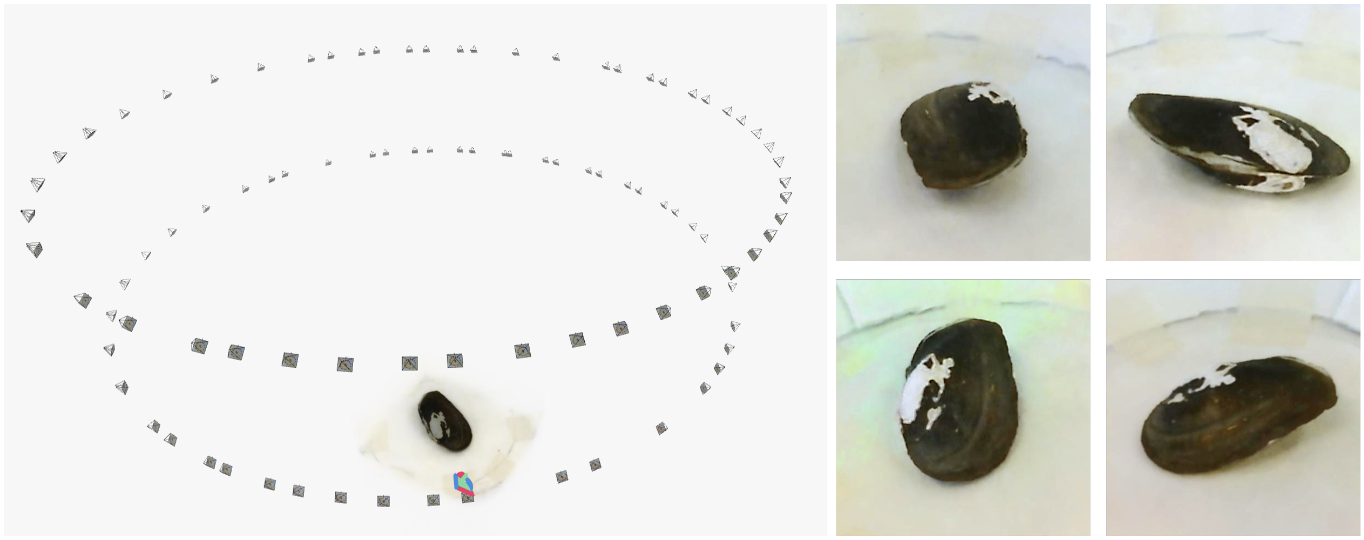

Fig. 3. Dual Ring camera position during reconstruction using NeRF (Exp 3) [left], and four newly generated views of the reconstructed mussel (*Elliptio complanata*) from Exp 3 [right].

of the COLMAP motion package [35] is used to estimate the camera parameters, i.e. to identify their location and intrinsic characteristics. Finally, a neural network learns a volumetric representation that can be used to generate new images given the location and orientation of a new camera using classical volume rendering techniques [20].

Nerfstudio [38] is a modular PyTorch framework for implementing NeRF based methods and streamlining the development and deployment of NeRF research. An extensible and versatile framework, Nerfstudio consolidates various NeRF techniques into reusable, modular components. It also enables real-time visualization of NeRF scenes with a vast array of controls while providing tools to export the reconstructed scene in the form of rendered videos or extracted point clouds and meshes. Nerfstudio documentation provides detailed steps for training various NeRF techniques using its methods.

Nerfstudio provides with a web-viewer packaged as a publicly hosted website as well as a wide range of tools to facilitate real-time visualization and interaction with the generated 3D scene during training or while evaluating a trained model [28] . The viewer can be accessed using both remote and local GPUs. The remote computing process is achieved by forwarding a port locally via SSH. The trained model can be rendered from various viewpoints, offering the ability to move the virtual camera around the scene. The camera positions, field of view, and lighting can be adjusted. The rendering properties such as resolution, anti-aliasing, and shading can also be fine-tuned to improve reconstruction quality. The interactive interface also includes options to explore the scene like zooming in or out, rotating or panning across the model, thus providing a detailed and dynamic view of the reconstructed environment. Finally, the export interface can be used to store the rendered scene into various export formats such as point clouds and meshes.

B. Mussel 3D Reconstruction

Given the setup shown in Fig. 1, the mussels are placed on the foam board with markers. The rotation of the board results in several images from the upper and lower cameras. Due to the way 3D reconstruction is performed, it assumes that the mussels is static and instead the cameras are moving. Our setup is equivalent to having a fixed mussel on the foam board with the cameras rotating around it forming an upper and lower ring. We take 59 images in total from each camera. Fig. 3 provides a perspective view of the calibrated cameras and the 3D reconstruction. A video of the reconstruction is available online at https://youtu.be/Asff8yX_VgY.

We consider three different experimental setups to evaluate the performance of 3D reconstruction with subsets of images coming from the upper right, lower right or both. For all of these, we take 8 consecutive images from the upper right, and 8 from the lower right as our testing set. In Experiment 1, from the remaining images from the upper ring, 43 images are designated for training and 8 for validation. Experiment 2 uses the same split but only with the lower ring images. Finally, both sets of images are combined in Experiment 3 resulting in 86 images for training and 16 for validation. This structured approach allowed for a comprehensive evaluation in different image configurations.

For our the evaluation, we make use of three commonly used metric for these applications:

- **Peak Signal-to-Noise Ratio (PSNR)** is defined as:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right),$$

TABLE II
PSNR VALUES FROM NERF RECONSTRUCTION

Metric	Training and Validation Set	Test - Lower Ring	Test - Upper Ring	Test - Combined (avg)
PSNR ↑	Upper Ring (Exp. 1)	22.7	**26.1**	**24.4**
	Lower Ring (Exp. 2)	**24.7**	23.4	24.1
	Both Rings (Exp. 3)	24.3	23.6	24.0
SSIM ↑	Upper Ring (Exp. 1)	0.89	**0.94**	**0.92**
	Lower Ring (Exp. 2)	**0.93**	0.87	0.90
	Both Rings (Exp. 3)	0.91	0.92	**0.92**
LPIPS ↓	Upper Ring (Exp. 1)	0.32	**0.20**	0.26
	Lower Ring (Exp. 2)	0.23	0.35	0.29
	Both Rings (Exp. 3)	**0.20**	0.23	**0.22**

where MAX is the maximum possible pixel value of the image (e.g., 255 for 8-bit images), and MSE is the mean squared error between the reconstructed image and the ground truth:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(I_{\mathrm{recon},i} - I_{\mathrm{true},i})^2.$$

PSNR measures the fidelity of the reconstructed image to the ground truth by comparing the signal strength to the error. Higher PSNR values indicate better image quality.

- **Structural Similarity Index Measure (SSIM)** is defined as:

$$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)},$$

where μ_x and μ_y are the mean intensities of images x and y, respectively; σ_x^2 and σ_y^2 are the variances of x and y; σ_{xy} is the covariance between x and y; and C_1 and C_2 are small constants to stabilize the division. SSIM assesses the perceived similarity between two images by considering luminance, contrast, and structural similarities. Values close to 1 indicate high similarity.

- **Learned Perceptual Image Patch Similarity (LPIPS)** is defined as:

$$\mathrm{LPIPS}(x, y) = \sum_l \frac{1}{H_l W_l} \sum_{h=1}^{H_l}\sum_{w=1}^{W_l} \|\phi_l(x)_{h,w} - \phi_l(y)_{h,w}\|_2^2,$$

where $\phi_l(x)$ and $\phi_l(y)$ are feature maps of the images x and y extracted from layer l of a pre-trained neural network (a VGG architecture was implemented by the *torchmetrics* [39] package used in Nerfstudio); and H_l and W_l are the height and width of the feature map at layer l. LPIPS evaluates perceptual similarity by comparing high-level image features, as opposed to pixel-level similarity. Lower LPIPS values indicate greater perceptual similarity.

From the results in Table II, it is evident that the performance in PSNR (higher values are better) depends on which training is selected. When the upper ring images were used for training and validation (Experiment 1), the PSNR was significantly higher for the upper ring test images (26.1) compared to the lower ring test images (22.7). Similarly, training and validation using the lower ring images yielded a higher PSNR for the lower ring test images (24.7) than for the upper ring test images (23.4). These findings highlight that the model achieves superior reconstruction quality when the test data closely align with the characteristics of the training data, but it has a harder time generalizing to data from different distributions. In contrast, using both upper and lower ring images for training and validation resulted in more balanced PSNR values across both test datasets. The PSNR for lower ring and upper ring test images were 24.3 and 23.6, respectively, with an average value of 24.0. While these values are slightly lower than those obtained with specialized training data, the balanced performance demonstrates the benefit of a diverse training dataset for improving generalization. This trade-off between specialization and generalization is critical, particularly in applications requiring the model to handle varied datasets effectively.

A similar trend was observed for SSIM. For LPIPS (where lower values indicate better performance) when both rings were used for training, the LPIPS values were a bit more consistent across both test sets, demonstrating improved generalization.

C. Long-Term Deployment Challenges and Sustainability

The long-term goal is to develop a real-time underwater monitoring system for continuous mussel behavior analysis in natural aquatic environments. We are planning to use the proposed 3D imaging system as a source of images to train the models for the underwater devices. However, several challenges must be addressed for effective deployment of the underwater system. One major challenge is underwater lighting variability, influenced by factors such as turbidity, depth, and ambient light fluctuations, which can impact imaging quality and AI model performance. Our 3D imaging system should mimic these conditions during imaging or after that through image processing, which is part of our future work.

Fig. 4. Juntos Summer Academy: (a) Students learning about the setup, (b) Building the imaging setup, and (c) One of the setups built by the students.

For the underwater system, the cameras and embedded hardware must be designed with robust waterproofing to ensure long-term functionality while maintaining optical clarity and sensor integrity. Power management is another critical consideration, requiring either an autonomous power source with extended battery life or an energy-harvesting mechanism to support continuous operation. Furthermore, data transmission presents a significant hurdle, as internet access is often unavailable in remote water bodies like rivers and lakes. To overcome this, alternative methods such as edge computing with local storage, low-power wireless networks, or periodic data retrieval strategies must be explored to enable seamless integration with cloud-based analytics platforms.

V. Educational Validation

The setup is designed to be user-friendly, making it easy for students, including those in secondary school, to create 3D reconstructions of their chosen objects. Both the embedded hardware and software are simple to build and implement. The necessary design files, source code and instructions for building and operating the system can be found online. To showcase its usefulness and ease of use, a team of high school students from the Juntos Summer Academy at NC State worked on this platform in the Summer of 2024, gaining hands-on experience in embedded hardware development, basic machine learning principles, and 3D reconstruction from 2D images.

Summer Academy is a five-day-long college experience held at NC State for rising 9th to 12th graders from across the state of North Carolina. In addition to participating in classes and workshops, attendees live on campus for a week, work closely with college students, professors, and professionals, and participate in a week-long project. Students attend career classes and skills workshops and participate in a networking mixer, college fair, and student group presentations for their projects. This formative experience allows students to experience the university as prospective college students, fostering curiosity and motivation for higher education and engaging in career exploration. Our platform was featured as a project for the engineering track at the Academy. We met with the students for approximately two hours during the five days of the event. Fig. 4 shows photos from the day that we spent building the platform.

At the end of the summer program, a survey was conducted. There were a total of 18 high school student participants in the track associated with this project with the following grade distribution: freshman (1), sophomore (4), junior (6) and senior (7). Six of them were first-time participants. The survey had many structured questions about the Juntos Summer Academy with an unstructured question associated with our platform: *"What, if any, skills did you gain from participation in this project?"* The responses revealed significant skill development and knowledge acquisition from the project. Key technical skills gained included coding, AI, networking, and 3D modeling, in addition students also learned hands-on applications of tools like ESP32 cameras. Many participants noted personal growth, including increased confidence, improved collaboration, and leadership skills. The project also enhanced awareness of AI's importance and its interdisciplinary applications, particularly in environmental science. While some students reported minimal learning, most responses highlighted the project's impact on both technical and interpersonal skills, showcasing the value of hands-on, multidisciplinary projects for fostering comprehensive learning experiences. The following are a couple of responses from students that capture these sentiments when prompted to provide what skills they gained from the project:

"I learned about how mussels help clean the water and how to build the ESP32 camera and the imaging system that helped us create an online 3D model of the mussels and the different ways this device can be helpful."

"I learned how to network and code and all about ai and 3D diagrams."

"I learned that AI is very important and helps us learn new things."

VI. Conclusion and Future Work

This project focuses on the transformative potential of integrating advanced technologies, such as Neural Radiance Fields (NeRF) and embedded systems, to study mussel behavior and enhance water quality monitoring, and uses this to create an impactful and accessible platform for STEM education. Mussels, with a potential to serve as natural bioindicators, play a critical role in aquatic ecosystems by filtering pollutants and reacting to environmental changes. By developing a cost-effective and reproducible 3D imaging system utilizing ESP32-CAM modules and servo motors, this study demonstrates a practical approach to constructing detailed 3D models of mussels in controlled settings. The synergy of advanced imaging techniques with embedded hardware not only advances environmental monitoring but also fosters STEM education by offering hands-on learning opportunities in AI, imaging, and embedded systems. This interdisciplinary initiative highlights the educational and environmental applications of cutting-edge technology. Future work aims to adapt this platform for underwater environments, refine AI models for real-time behavioral analysis, and broaden collaborations with educational institutions to amplify impact. Ultimately, this research exemplifies the promise of integrating bioindicators with innovative technologies for sustainable environmental stewardship and education.

Our future plans include the refinement of this tool through further technical evaluation of the platform and its impact for outreach. We plan to expand on these efforts by partnering up with other K-12 outreach programs such as The Engineering Place [36] and the Science House [37] at NC State for summer camp and year-around activities. Furthermore, the validation performed in this study was mainly qualitative. We will considered more structured metrics such as the use of quantitative surveys to better quantify their impact.

As part of our dissemination efforts, we will also work on additional resources to help students and STEM enthusiasts to build such platforms in publicly accessible makerspaces. University or library makerspaces have added a new dimension to student learning through hands-on projects that help students build a wide range of skills otherwise underdeveloped [12] and support diversity and inclusion [18], [32]. Student engagement (voluntary or through courses) is associated with higher STEM identity [23], GPA [17], and engineering design self-efficacy [18]. The maker movement started outside of academia with the Do-It-Yourself (DIY) culture [3], which some consider a form of citizen science and lifelong learning environment [13]. Given the research context of our platform, students and members of the public could build the platform in makerspaces and use it to generate more images as part of a larger project for an AI monitoring sensor system based on mussel behavioral responses to water quality.

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