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A Compact Smart Greenhouse for STEM Education: Proof of Concept for Sustainable Food Provision

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ABSTRACT

Sustainable and efficient agricultural production methodologies are essential for the future, relying neither on land area nor manual labour. This project presents an aquaponic greenhouse model designed for STEM education, particularly in physics, chemistry, and ecology. A computer vision module developed via deep learning serves as a proof of concept for automating the data collection and monitoring of ecological variables relevant to fish and plant health within the greenhouse. The system can be extended to accurately control these variables using an artificially intelligent model. Future development will include the non-invasive measurement of microorganism and ion concentrations using spectroscopy, and the application of more rigorous data collection and data analytics.

Introduction

Hydroponics and Aquaponics

The term 'hydroponics' refers to the soilless cultivation of plants using an aqueous solution of mineral nutrients (Khan et al., 2020). The combination of hydroponics and aquaculture gives rise to aquaponics, which is analogous to a circular economy (Estim et al., 2020). Aquaponics aims to cultivate fish and plants symbiotically, thereby reducing the system's reliance on human intervention and conserving nutrient resources.

Current hydroponic and aquaponic models have demonstrated significant potential in economising land and water use, as well as offering versatility in customising plant growth environments and system mobility (Somerville et al., 2014) through vertical farming. Nevertheless, special attention is required to maintain a compact environment conducive to the efficient growth of both flora and fauna. In aquaponics, this is complicated by the fact that conditions favourable for plants may disturb the aquatic environment, leading to fish intoxication and vice versa. For example, un-ionised ammonia from protein digestion and excretion can induce the secretion of cortisol (a major stress hormone (Sadoul and Geffroy, 2019)) and glucose (indicative of stress (Polakof et al., 2012)). High ammonia concentrations can cause fish death (Carneiro et al., 2009). However, ammonia can be biologically converted into nitrites by Nitrosomonas and subsequently into nitrates by Nitrobacter (Anthonisen et al., 1976). Nitrates provide an ample supply of nitrogen to plants in a readily absorbable form (Näsholm et al., 2009), reducing the toxicity of tank water, decreasing the frequency of water changes, and minimising waste. Nitrogen is also a primary macronutrient in horticulture (Bamsey et al., 2012; Bregliani et al., 2005). Meanwhile, plant roots 'clean' tank water, promoting efficient aquaculture. Consequently, aquaponics offers a more sustainable and economical alternative to traditional methods of cultivating flora and fauna. It also advances vertical farming practices, saving land (Kholis et al., 2021) and reducing the dependence of plant growth on local weather conditions (Estim et al., 2020; Sardare and Admane, 2013; Somerville et al., 2014), for instance. This approach is embraced by governments, investors, and entrepreneurs (Kholis et al., 2021) to address socioeconomic challenges such as a rising demand from an ever-growing urban population (Al-Kodmany, 2018; Khan et al., 2020) and regional water shortages (Sharma et al., 2019; Khan et al., 2020).

Three Greenhouse Models

Three greenhouse models were constructed in this project. The first version, which was hydroponic only, was built for preliminary experimentation with basic environmental conditions (e.g., light intensity and wavelength, ionic concentration, and air ventilation). This version modelled a vertical-farming setup, consisting of stacking layers of plants. Fish were added for the second and third models, motivated by the presence of an existing fish tank within the laboratory space, leading to a transition from hydroponics to aquaponics.

Several hydroponic methods were employed, namely drip irrigation (DI), deep water culture (DWC), and nutrient film technique (NFT). For DI and NFT, a timer was used to promote root respiration, noting that the process of root ionic uptake is highly energy-demanding (Yamori, 2020) yet essential for the transport of nutrients to other parts of the plant. The timer allowed plant roots to come into contact with atmospheric oxygen, enabling the oxidation of sugars and subsequent energy release. As such, the DWC method, while beneficial for fruit-producing plants like cucumber (species *Cucumis sativus*) and tomato (species *Solanum lycopersicum*) (Sharma et al., 2019) due to their high nutritional uptake, requires the inclusion of aerators to compensate for the slow oxygen exchange between the solution and the environment. NFT balances the two methods by submerging the plant roots within the nutrient solution for a limited time, although more space was required to contain an NFT system. The species cultivated in the greenhouse were green salads (species *Lactuca sativa*) and tomatoes.

Fish species were initially chosen based on accessibility and affordability, such as Koi fish (species *Cyprinus rubrofuscus*), rainbow fish (family *Melanotaeniidae*), and sailfin molly (species *Poecilia latipinna*). However, due to high mortality rates, they were substituted with tinfoil barbs (species *Barbonymus schwanenfeldii*), angelfish (genus *Pterophyllum*), and tiger barbs (species *Puntius tetrazona*), which could better tolerate the aquaponic environment. These fish were fed protein and fibre through commercially bought food pellets. The digestion of protein produced ammonia which would then be excreted. At the pH level of the nutrient solution, the ammonia mostly dissociated into harmless ammonium ions. This is because the pK_a value for ammonia is about 9.25 (Bates and Pinching, 1949; Perrin, 1982), which is also the pH value at the half-equivalence point. Since the pH value of the solution (tested to be between 6 and 7) is lower than the pK_a value, the equilibrium lies mainly to the left side. However, a high actual amount of ammonia could become toxic and had to be removed.

$$NH_4^+(aq) \leftrightharpoons NH_3(g) + H^+(aq)$$

Two filters were created: one for removing suspended solids (made of cotton) and one for biological conversion. The latter involved running the raw-filtered solution through clay pellets where the bacteria could develop. The conversion efficiency increased gradually over time as the bacterial population grew, which was confirmed through regular tests conducted with the Sera NO_3 test kit. This evidence suggests that Nitrosomonas and Nitrobacter could naturally grow and multiply.

Automation

The next step recognised that the ecosystem was entirely dependent on human care, which may not always be feasible. A Raspberry Pi 4 (RPi) (Raspberry Pi, n.d.) was chosen to control the network of sensors and actuators for several reasons. Firstly, the board can be connected to a screen, allowing for data display and user interaction with the digital system. Secondly, the RPi operates as a computer using the Raspbian operating system, providing the greenhouse with compactness and software flexibility. Thirdly, Grove connectors are used to connect sensors and actuators to the RPi via a GrovePi+ Shield, eliminating the need for soldering (Dexter Industries, 2016) and increasing wiring safety. This considerably speeds up the hardware setup process. Lastly, the programming language Python could be quickly written, compiled and executed on an RPi, and was also supported by the grovepi library (Dexter Industries, 2016) for reading inputs from sensors and sending outputs to actuators.

Several variables are measured. External light intensity is monitored using a Grove Light Sensor (LS06-S photoresistor) (Seeed Studio, 2024b) positioned on the outside surface of the greenhouse to avoid registering the artificial lighting inside. A Grove Soil Moisture Sensor (Seeed Studio, 2023b) measures the humidity level in the coconut coir of a plant, while a Grove Temperature and Humidity Sensor (DHT11 sensor) (Seeed Studio, 2023a) records the air temperature and humidity.

Semi-automatic environmental control was enforced using actuators like ventilating fans, water pumps, blue-violet lights, a fish aerator pump, and a food feeder. These actuators were controlled by Grove Relays (Seeed Studio, 2024a) connected to the Rpi.

Human supervision was facilitated through the development of a user-interface dashboard based on the loT platform Thingsboard (Thingsboard, n.d.). The host was local as the project was a proof of concept, and the dashboard was displayed on a screen attached to the exterior surface of the greenhouse. Alarms were activated using pre-set numerical thresholds (as upper or lower limits) for different variables, and visualised graphs showed these thresholds and the state of each actuator (e.g., lights on or off).

Various processes were automated. UV lights, controlled via a Grove Relay, would turn on when the illuminance of light (measured in lux) detected by the Grove Light Sensor fell below a minimum level. The measured light originated from both sunlight and indoor lighting. Additionally, a pump was activated when root moisture levels dropped below a threshold to replenish the nutrient supply. A water sprayer released fine droplets to regulate the temperature and humidity inside the greenhouse. All electronic devices, including the sensors and actuators, were protected from water exposure. A ventilation fan operated at all times to maintain a constant supply of oxygen and carbon dioxide for respiration and photosynthesis, respectively.

Computer Vision

The cultivation of fish and plants generated a vast amount of data, which was used to train and validate computer vision (CV) modules for supervising fish. To optimise these modules for execution on an RPi, a balance between run-time performance and system requirements was crucial. Potential models included ResNet, EfficientNet, and MobileNet for TensorFlow; YOLO and Inception for PyTorch; and others hosted on platforms like Darknet and Caffe (Politiek, n.d.). Using the OpenCV library (OpenCV, n.d.) and a YOLO-based deep neural network (DNN), a CV programme was developed to monitor fish movements.

Spectroscopy

Currently, the project focuses on non-invasively analysing the ionic composition of tank water through spectroscopy. Spectroscopy is a more environmentally-friendly, economical, and efficient alternative to reagent-based testing methods, which may cause ecological damage upon discharge, cannot be conducted continuously, and are expensive to maintain. Since visible absorption spectroscopy failed to provide useful information, Raman spectroscopy is being investigated.

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Ethical Considerations

Finally, it is important to consider the ethical implications of working with living organisms. As the prototype was developed alongside a literature review of academic and experiential publications on aquaponic cultivation, some fish and plant deaths were unavoidable during the research process. Causes of fish deaths involved severe physical injuries, ammonia intoxication, fish leaping out of the water and suffocating, and diseases. For plants, caterpillars feeding on leaves and roots caused minor damage. Temporary shortages in the concentrations of some elements in the nutrient solution led to yellowing leaves and the death of a small number of plants.

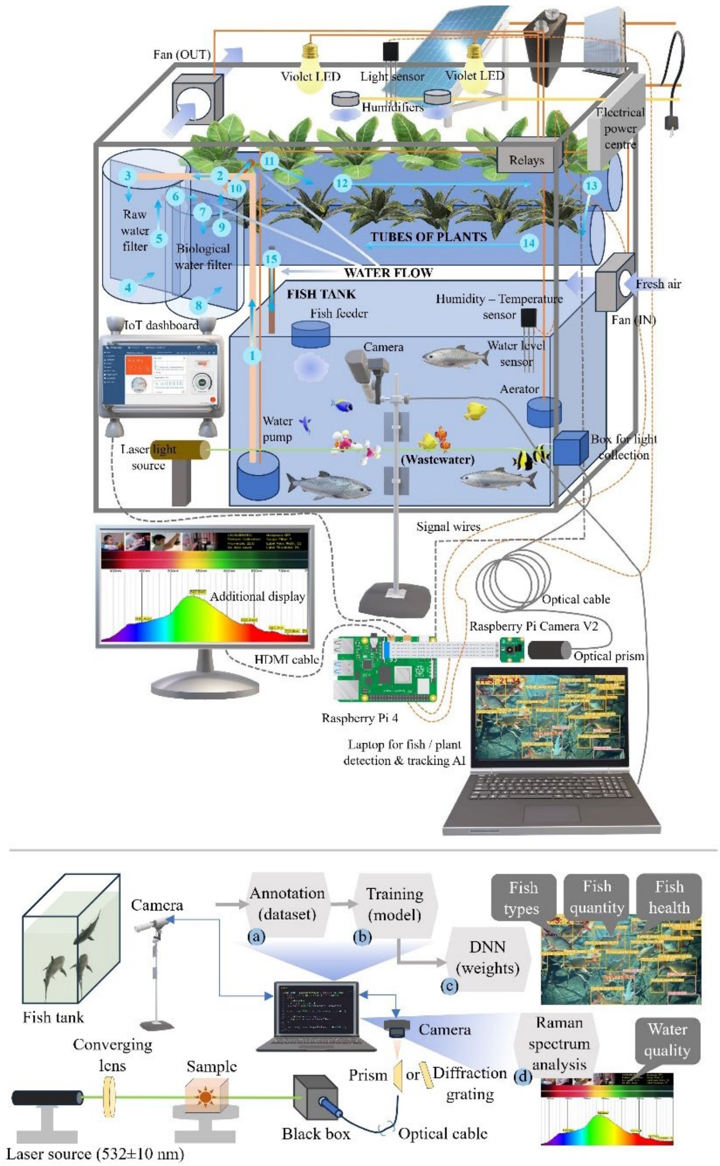

Figure 1. A schematic diagramme for the greenhouse.

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Project Development Phases

Designing an Aquaponic Greenhouse

The first hydroponic model was built from scratch using PVC water tubes. Hydroponic baskets filled with coconut coir were used to support plant roots (for all three hydroponic methods), retain water, and provide nutrition (for drip irrigation and NFT). Each basket was placed in a fitting hole on a PVC tube, allowing the nutrient solution to flow inside the tube and be absorbed by the roots. A pump delivered the nutrient solution from a tank at ground level to the PVC tubes. This pump was regularly turned on and off at fixed intervals to promote root respiration. Green salad was the first species cultivated. After a month, the salads were harvested and were edible, with a green leaf appearance resembling traditionally cultivated green salads.

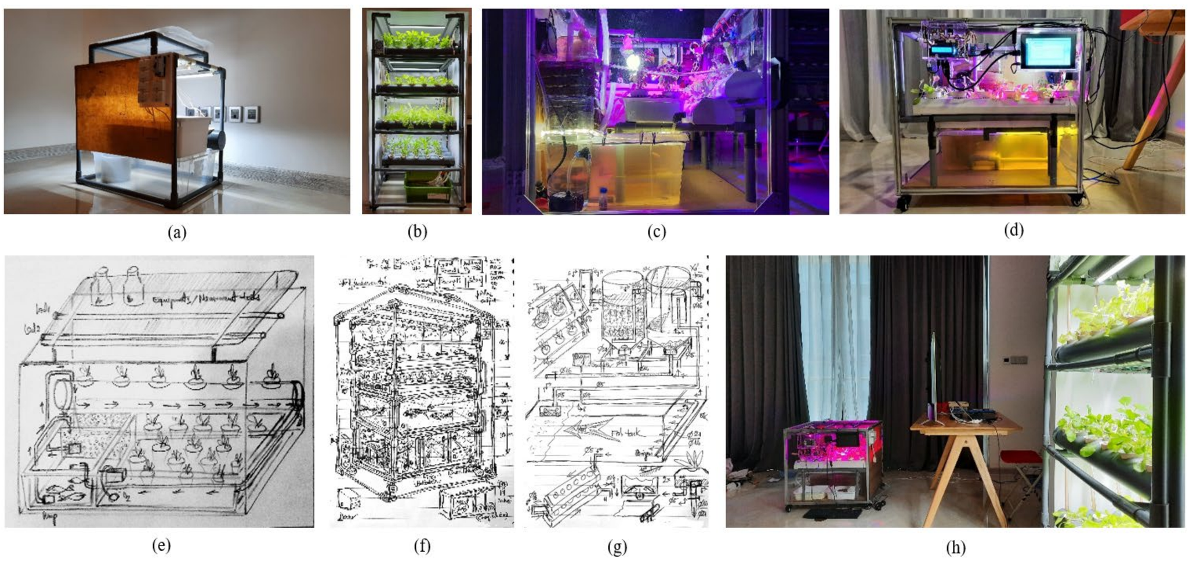


Figure 2. The development and deployment of ideas throughout the project. Drawings (e), (f), and (g) are three designs corresponding to the three greenhouse versions. Images (a), (b), (c), (d), and (h) are real footage of the greenhouse.

Developing a CV System for Monitoring Environmental and Growth Variables Inside the Greenhouse

To optimise training performance, some existing datasets from the Roboflow platform were selected for testing (Roboflow, n.d.). Figure 3 shows the trained weights returning problematic results, attributed to low-quality annotation. In particular, wrong and missing labels were commonly encountered, and many photos had bounding boxes that did not tightly align with object edges (see Figure 4 for an example). Passing the Fall Detection Object Detection (FDOD) dataset (7784 images, image size 416×416) (Roboflow, 2023) through a YOLOv8m neural network yielded no significant changes in mAP after 88 epochs. Even after 50 additional epochs, the model still carried significant errors, despite an improvement in results.

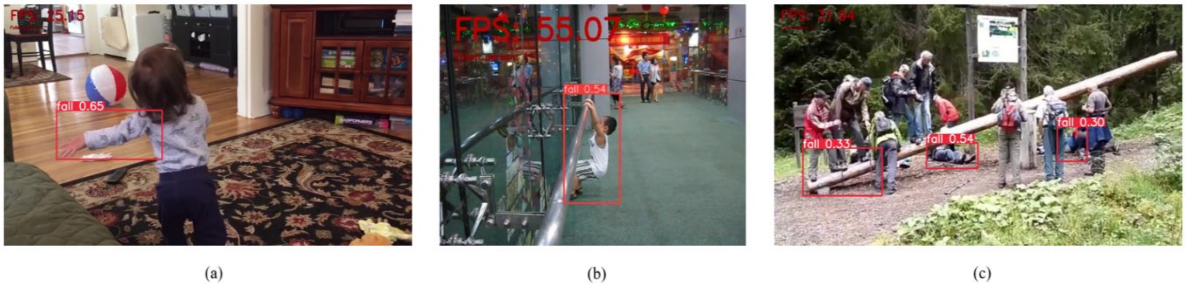


Figure 3. Some wrong results from YOLOv8m, being trained with the FDOD dataset (Roboflow, 2023). Images (a) and (c) were taken from the FDOD dataset, while image (b) was a frame cut from a personal video of the authors.

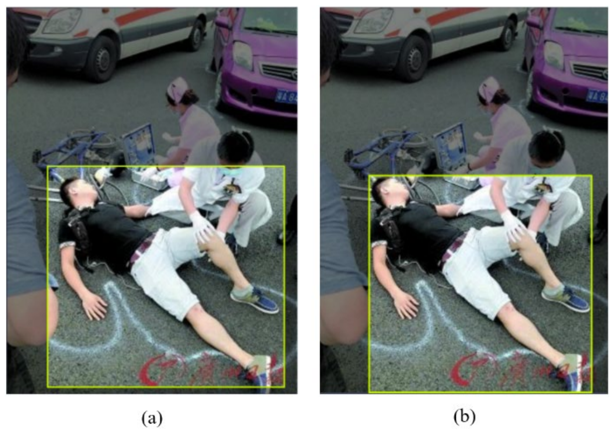


Figure 4. Illustration of what is meant by 'bounding boxes tightly bounding onto object edges.' Image (a) was taken from the FDOD dataset (Roboflow, 2023). Image (b) was edited from (a) to exemplify an 'ideal' bounding box.

The quality of data was emphasised. Online and self-taken footage of tinfoil barbs, angelfish, and tiger barbs, captured from various viewing angles under different lighting conditions, were collated and carefully annotated to ensure bounding boxes were 'tight.' (see Figure 4 for an example). This dataset comprised 850 images in total with four class objects, or tags. The first three tags belonged to tinfoil barbs, angelfish, and tiger barbs, respectively, while the fourth class consisted of all other species under the umbrella term "Fish."

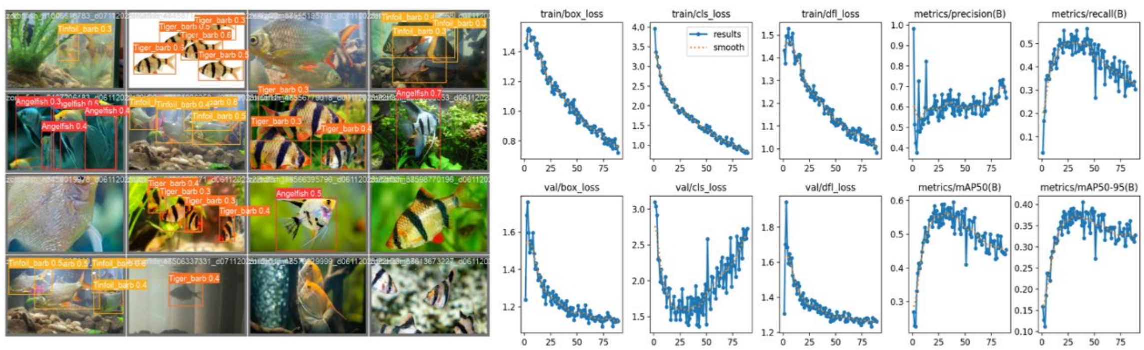
Since the neural network only accepted numpy arrays (see NumPy (2024) for an overview), all images had to be resized to the same dimensions. Portions of an image not within bounding boxes were removed to allow for resizing. The dataset was subsequently randomised to avoid catastrophic forgetting. The presence of each class was balanced to ensure final weights would reflect all classes equally, and the dataset was divided into training (83%) and validation (17%) image sets.

Due to inferior detection results, the dataset size was expanded to about 2000 images with varied camera angles, lighting conditions, amounts of noise, and fish quantities. Better prediction performance was observed with the same number of epochs, but class misclassification remained common. The next step was to familiarise the neural network with the detection background of the greenhouse. More than 600 images were captured, annotated, and added to the existing dataset, creating a final dataset of 2614 images.

A preliminary test involved training a set of weights on NOAA's Deepfish dataset (DeepFish, n.d.) for 100 epochs. To study the influence of a network's memory on performance, an experiment was conducted where the final dataset was passed through both a new 'yolov8n.pt' model and a pre-trained model, 'deepfish_100ep_zorbafish_50ep.pt.' The mAP_{50} values peaking at 0.43 (mAPso:$_{50}$ ≈ 0.33) and 0.82 (mAPso:$_{95}$ ≈ 0.67), respectively (see Figures 5 and 6). The yolov8n.pt model was selected as the lightest YOLOv8 version to optimise performance on an RPi.

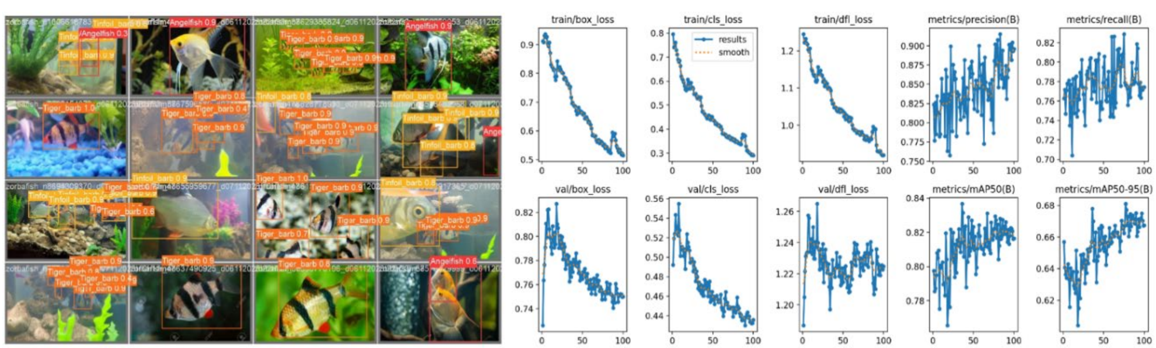
Figure 5 suggests that the new model (yolov8n.pt) suffered from overfitting after about 30 epochs, as indicated by the plateaus on the mAP_{50} and $mAP_{50\text{-}95}$ graphs. In contrast, the pre-trained model (deepfish_100ep_zorbafish_50ep.pt) did not reach a plateau on either of these graphs, with the mAP_{50} and $mAP_{50\text{-}95}$ values still showing an increasing trend after 100 epochs.
Moreover, at the same number of epochs, the pre-trained model generally displayed superior performance in terms of mAP compared to the new model. Therefore, it can be inferred that prior learning improved the model's prediction accuracy.

Both models recorded a very low mean frame rate per second (fps) of about 1. This value increased to roughly 1.7 fps after cleaning the cache storage and RAM. To further improve performance, the neural network was changed from YOLOv8 to YOLOv5, removing some unused features and retraining the network on the same dataset. A conversion from PyTorch to TensorFlow Lite raised the mean frame rate to approximately 4 fps.



(a) (b)

Figure 5. The collection of images (a) shows examples of real detection results. The charts in (b) displays changes in different training and predictive metrics for yolov8n.pt, trained with a dataset of 2614 images (83% train & 17 % validate). The horizontal axis conveys the number of epochs from 0 to 89 (the total number of epochs used). The vertical axis represents the quantity given in the title of each corresponding graph.



(a) (b)

Figure 6. The collection of images (a) shows examples of real detection results. The charts in (b) displays changes in different training and predictive metrics for deepfish_best_100ep.pt, trained with a dataset of 2614

images (83% train & 17 % validate). The horizontal axis conveys the number of epochs from 0 to 100 (the total number of epochs used). The vertical axis represents the quantity given in the title of each corresponding graph.

Analysing Water Quality Using Spectroscopy

Due to concerns regarding the environmental impact and cost-effectiveness of invasive methods for identifying ions in water, such as drain discharge and a lack of continuous water tests, it is imperative to explore non-invasive alternatives. Spectroscopy is selected as a promising option due to its sensitivity and ability to discriminate between specific aqueous ions.

Following preliminary experimentation and review on the NIST Chemistry WebBook database (National Institute of Standards and Technology [NIST], n.d.), visible absorption spectroscopy was founded to be impractical due to a lack of absorption bands. The focus has thus shifted to investigating Raman spectroscopy as a viable technology. Detailed findings from this investigation will be published in due course.

Monitoring Fish Health Using Pose-Estimation CV

Monitoring fish health, in contrast to plant health, is complicated by movement. However, early intervention is crucial for administering treatments for diseases and controlling their spread by isolating infected fish. For this purpose, a preliminary pose-estimation model based on YOLOv8 was tested.

(a) (b) (c)

Figure 7. Experimentation with pose estimation using YOLOY8m-pose.pt. Images (a), (b), and (c) were frames taken from a personal video of the authors.

By identifying 17 key points, the distance between each pair of key points could be measured, allowing the neural network, named yolov8m-pose.pt, to learn and generate predictions. However, these distances depend on the viewing angle and frame resolution. An approach under exploration is to consider all distances as ratios rather than individual variables. Nevertheless, since there are more ratios than variables to consider per frame, this technique may increase the computing power required. Performance optimisation will hence be essential in the future and the subject of future investigation.

Conclusion

In this project, three greenhouse models have been constructed. A semi-automatic aquaponic cycle was successfully implemented, and object-detection and pose-estimation CV modules targeting fish were developed. Biological filtering also allows for the conversion of ammonia to nitrites and then nitrates, preventing fish intoxication and reducing food waste products. Moreover, the project incorporates a range of digital technologies to reduce the need for human supervision during the food production process while enhancing it. These technologies range from the monitoring of environmental conditions using sensors, actuators, and an interactive dashboard to an object-detection CV module. The successful implementation of a semi-automatic system for quantitative data acquisition and data-driven optimisation of aquaponic conditions demonstrates the high level of compactness and automation that a greenhouse can achieve through the utilisation of hydroponics and aquaponics.

In the future, more sensors measuring existing and new variables will be added during the deployment process of the greenhouse model. Additionally, Raman spectroscopy, along with other spectroscopic techniques, will be investigated to non-invasively analyse the ionic composition of tank water and integrated into the current semi-automatic system. Further research into pose-estimation CV will be conducted to develop a health diagnostic system for fish.

The project seeks to develop a compact and smart greenhouse model using materials accessible to high-school students. The authors believe that since all high-quality scientific devices started from convenient materials and tools, expensive and advanced equipment can be substituted by ingenuity, perseverance, and guidance to foster scientific thinking and hands-on learning. With a vision of making practical STEM education available to everyone, this project aims to become non-profit and advocates for inclusivity, fairness, and social impact in educational opportunities, transcending and eradicating discrimination.

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