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Design and Development of a DIY Photo-bioreactor for Optimized Microalgae Cultivation and Sustainable Biomass Production

Youssef Mohamed [1], Radwa Kamal [1], Ziad Abd-El aal [1], Zahra Hussein [1], Ahmed Gomaa [*]

[1] faculty of biotechnology, October University for modern science and Arts, 6th October, Egypt

[2] RDI Lab

***** Correspondence: youssef.mohamed68@msa.edu.eg

Abstract: The emerging use of microalgae as a potential source of biofuels, medicine, and even in pollution control has made the growth and culture of microalgae one of the fastest growing fields in the biotechnology world today. This paper develops a low-cost DIY photobioreactor (PBR) controlled by artificial intelligence (AI) for efficient microalgae growth and biomass production. Some important problems in microalgae production such as contamination, poor CO_2 conversion efficiency and high energy demand are solved by faster R-CNN (Region-based Convolutional Neural Networks) to detect and remove the contaminants and bio-integrated detection control system. The photobioreactor was designed using computer software and manufactured with equipment including RGB lights, temperature indicators, and CO_2 indicators. AI integration enabled real-time monitoring of microalgae species and obtained a better approach to species detection and classification. The results proved that the culture attached to Spirogyra microalgae was successful, and the AI models yielded fairly high accuracy in species prediction and shapes. The developed system also provided a comprehensive graphical user interface (GUI) to manage and observe the environmental parameters in real time. The present work focuses on DIY biology and AI capabilities for microalgae research, and suggests the use of open source tools and technologies for biomass production, environmental remediation, and other sustainability solutions.

Keywords: Photobioreactor (PBR), Artificial Intelligence (AI), PID control, DIY, Faster R-CNN. Microalgae

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1. Introduction

In recent years, this type of microorganisms has become important for its versatility, and mainly due to the ability to produce biomass. Some of the major problems experienced in algal biotechnology are the improvement of biomass production, and industrial growth of

photobioreactor. The DIY photobioreactor system with the integration of AI will help to avoid the facing challenges of differentiation and classification seen in microalgae by this research [1]. Centrifugally grown photosynthetic microorganisms that can reduce CO2, nutrients and build organic structures and oxygen, microalgae have also boosted food, bio-fuels and other productions owing to high growth rates and high efficiency of removing unwanted nutrients from water sources [2].

Microalgae are unique cells that are useful in bioremediation, bio agriculture, health and energy. Due to their high lipid content, and their capacity to grow relatively fast they are suitable for biodiesel production. Furthermore, the microalgae are used as a food supply rich in formal nutritional ingredients such as, essential fatty acids, proteins, and vitamins. On the pharmacological level, they contribute bioactive compounds with bactericide, anti-inflammatory, antioxidant effects, the function of removing pollutants such as heavy metals and nutrients from wastewater makes them a fundamental component of environmental rehabilitation [3].

PBR's stand for photobioreactors, which are sophisticated systems used to grow microalgae in a defined environment with light, temperature and nutrients. PBR's are superior to open systems in a number of ways, including higher biomass yields, better environmental control, and less chance of contamination Enclosed reactors, including those that come in tubular, flat panel, and column configurations, give better controllability of light distribution, temperature and gases, which in turn enhances system efficiency. But such systems are costly for development and implementation, so the demand for more efficient solutions remains high. PBR technolo-gy improvement has been concerned with optimizing the usage of energy and mass in large scale algae cultivation for biofuels and other co-products. According to the survey conducted by Ab-del-Raouf, Al-Homaidan & Ibraheem in their meta-analysis in 2012 [4].

Some of the difficulties associated with large-scale microalgae production are contamination, poor Carbon dioxide capture, and energy consumption. Such open systems especially the raceway ponds are always at high risk of contamination and calls for highly pure systems. The enhancement of capturing and delivering CO_2 still has to remain a pivotal focus to increase the rate of photosynthesis and yields on biomass. These challenges can only be solved with better technology such as energy efficient photobioreactors and optimized nutrient supply; otherwise, the microalgae will remain a less explored but highly sustainable resource [5].

About DIY biotechnology, the researchers have been able to come up with low cost solutions for work on microalgae. For example, Phenobottle, a low-cost photobioreactor containing raspberry pi technology allows recording the photosynthesis continuous and growth of green algae and cyanobacteria. These DIY advancements have enabled new practical uses in biofuels, pharmaceuticals and environment via features such as light diffusion and instant data analysis [6].

Faster R-CNN, a deep learning-based object detection framework, has been used to accurately identify and quantify microalgae species from microscopic images. This leads to better detection efficiency due to the better feature extraction and localization ability possessed by the proposed system. On the other hand PID control system controls growth parameters like light, CO_2 and

nutrients. However, even with PID control systems, problems arise concerning species differentiation and precision. Combined with PID control systems, Faster R-CNN can improve microalgae detection successfully because AI related to the improved classification performance [7].

This project outlines a strategy that may be applied to address inefficiencies in biomass yielding for bio-energy and application in environmental management and biotechnology to do away with the problems like high costs, low nutrient recycle ratio and contaminations. The Do-It-Yourself photobioreactor that uses artificial intelligence for monitoring temperature, CO_2, light, and nutrient will help make the process more productive as well as eliminating unnecessary waste products. This initiative seeks to develop affordable, scalable photobioreactor systems that optimize cultural and environmental factors while achieving high detection accuracy through the Faster R-CNN and PID control integration. The ultimate goal is to democratize this technology, encouraging research and innovation in biofuels, environmental solutions, and biotechnological advancements.

2. Materials and Methods

2.1. Cultivation Setup for microalgae cultures

The procedures of cultivating Spirogyra were started by collecting Spirogyra from the National Research Centre (NRC) with the confirmation of their sterile and healthy state. The appropriate growth media formula was to contain high nutrient concentration; ideal recipes comprise of Bold's Basal Medium (BBM) or natural freshwater containing minimal nutrient concentrations. For a bioreactor with a 200 mL capacity, BBM was formulated by dissolving the following per 200 mL of distilled water: It consisted of $NaNO_3$ (50 mg), K_2HPO_4 (15 mg), KH_2PO_4 (35 mg), $MgSO_4 \cdot 7H_2O$ (15 mg), and $CaCl_2 \cdot 2H_2O$ (5 mg) and other trace metals and vitamins as used in Lloyd et al. (1/5 th of BBM). The medium was then sterilized using autoclave at 121°C for 15 minutes. Instead, natural freshwater washed the leaves with pond water or diluted fertilizer solution like 10% Hoagland's solution, respectively. Environmental conditions were controlled to optimize growth, with moderate light provided at 100–200 μmol photons m^{-2} s^{-1} using either natural sunlight or artificial light on a 12:12 light-dark photoperiod. It was kept at 20–25 °C and the culture was mixed carefully so that the filaments did not settle at the bottom and nutrients were adequately broadcasted across the entire tube but without so much bubbling that it hindered the filaments. pH of the water was maintained at 7 to 8 with medium being changed once in a week to avoid buildup of wastes. Daily observations were conducted on the density of filament and its growth this was accompanied with microscopic inspection on the characteristic spiral chloroplasts to see whether the switch was healthy or not. Morphologically different fungi or other type of algae, which could possibly interfere with the observation, were either mechanically rinsed off or filtered out with minimal pressure.

2.2. Designing and Assembling the Prototype of the photobioreactor

The prototype was designed using a free software called 3D Blender where the outer layer of the photobioreactor was contracted at a length and width of 20cm and 15 respectively.

After the parts were printed, ESP-32-wroom-32 was placed inside its designed container which was glued shut. Afterwards, the glass container was placed in the designed place for it where the RGB lights available and directly aimed toward the glass container containing the microalgae, also, the heater was placed under the glass container to support the strain with the specific temperature needed, along with three different fans were assembled in the design, two of them were in the upper part of the photobioreactor in order to supply sufficient cooling to the strain when needed, and the third fan was placed in the lower part of the photobioreactor in order to apply sufficient cooling to the ESP chip in case it went into over-heating circumstances, the rest of the compartments were placed in the lower part including the temperature sensor and the pH sensor and the CO2 sensor and Humidity sensor, as for the led, It was added on-top the photobioreactor where it was designed to contain 3 tubs of in-let and out-let. also, the led and the upper part and the lower part of the photobioreactor were attached to each other using magnetics that had specific places that were included to the design

2.3. Creating the Machine Learning Dataset for image processing

The PID control and Faster R-CNN were deployed with the aim of increasing the identification process and the photobioreactor analysis quicker in the algorithm introduced for the microalgae analysis. All the PID control script was developed using VS Code and a library added to import the benchmark and sample photos. In an effort to improve the performance of the PID control model, it was trained for 20 epochs in this study. In order to widen the use of the program, Roboflow was used for data processing for Faster R-CNN functionality. Upon compiling the data, the next step was to structure the workflow by opening a new environment at the Command Prompt and installing Jupyter Notebook. It is of the same defining images that another set of images was used to train another set for the Fast R-CNN model with the results being recorded into the Jupyter Notebook, after reaching the 250th different images. These strategies enhanced the detection system for photobioreactors highly in identifying the diameter, type, strain, and family of the microalgae.

2.4. Training the Machine Learning Model

A classification model using advanced methodologies for accurate detection of microalgae within the photobioreactors was also designed using the machine learning model. PID control framework was trained on a high-resolution image set filtered to enhance feature definition and homogeneity. There were utilized pre-process and adjustment tools, namely Roboflow to integrate the Faster R-CNN model. The database of 250 segmented images was augmented to reduce data bias and amendment of overfitting issues. The data was divided as 80% of the samples for training and 20% for validation based on a Stripes of 80/20. Thus, stochastic gradient descent optimizer was used to fine-tune the model. , basic performance measures including mean average precision and intersection of union were used during training to achieve high precision. The creation of the model was done in a separate space on VS Code, while Jupyter Notebook was used in model assessment and representation. The trained model was fairly well optimized to respond with high accuracy in its classification and detection performances. This work was outlined as a contribution to algal biotechnology and bioengineering disciplines.

2.5. Designing the Graphical User Interface (GUI)

The GUI was developed using megunolink were input systems were developed to control and monitor all functions in the device including increasing or decreasing the percentages of the temperature, CO_2 levels, and PH levels as well as humidity and colors intensities (RGB Lights) that allow selective control of the photosynthesis levels required by the microorganisms in a different situations by the time which are indicated by the monitoring the graphs and curves that were designed also in the GUI were they connect to the device via specific code that was pre-designed that transmits the viability state of the cells as well as the parameters imbedded in the device's hardware. Moreover, a real-time monitoring was developed to monitor the changes made by user

3. Results

3.1. Cultivation Setup for microalgae cultures

The cultivation procedures for the Spirogyra were successfully followed. Prior to the process, the Spirogyra samples from the NRC were found to be sterile, healthy, and free of contaminants. The prepared Bold's Basal Medium (BBM) favored growth of the seeds, and there was no contamination throughout the experiment. Environmental conditions were effectively controlled by maintaining temperatures between 20-25°C and providing light at 100-200 µmol photons m^{-2} s^{-1} on a 12:12 light-dark cycle. The developed culture maintained its growth at steady rates, and the filaments were well dispersed and uniformly distributed by proper mixing. The pH was found to be in the range of 7 and 8 at all stages of cultivation. It was therefore possible to effectively reduce waste accumulation while ensuring available nutrients through weekly medium changes. No morpho pathological changes were observed histologically, the filaments were tightly packed with healthy filaments, and further reproduced through spirally shaped chloroplasts. Washings and mechanical filtering respired the contaminants including fungi and other algal species. These results are a positive assurance of the efficiency of the cultivation setup to support the growth of Spirogyra in a mannered environment.

3.2. Designing the photobioreactor

After using 3D blender, the prototype was separated into 5 parts as shown in figure (1)

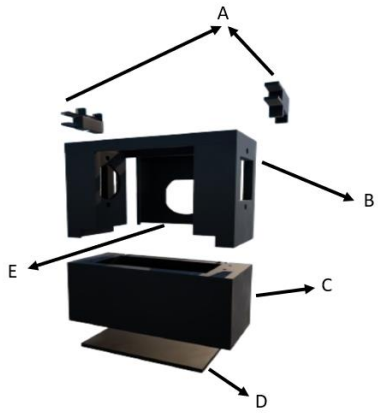

Figure [1]. Represents the final shape of the prototype design after the rendering process is over, (A) represents the fans supporters, (B) represents the upper part of the photobioreactor, (C) represents the lower part of the Photobioreactor, (C) represents the cover on the bottom part that holds all the electronic circuits including ESP chip and circuits from all the sensors, and (E) is the back-cover that support the RGB lights' board

3.3. Assembly of the photobioreactor

Upon the printing process the working model parts emerged and placed together as can be seen in Figure (2).

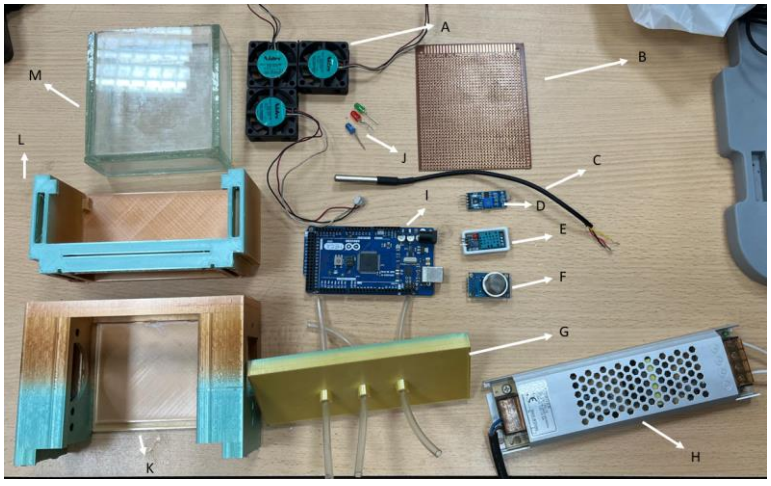

Figure [2] shows assembly of prototypes compartments, (A): cooling fans, (B): circuit for RGB lights, (C): temperature sensor, (D) humidity sensor, (e) pH-sensor, (F) CO_2 sensor, (G) cover lid, (H) power supply, (I) RGB Lights, (J) Arduino chip, (K) upper part, (L) lower part, (M) glass container

Figure [3] shows the final shape after being assembled

3.4. Creating the Machine Learning Dataset for image processing

In order to decipher the patterns of microalgae species, spatial distribution and morphological distribution, the presented data visualizations were analyzed. The bar chart showed the number of instances for five microalgal taxa, where it was found that most of the microalgae belonged to Chlorophyta and Cyanobacteria, and few numbers of microalgae belonged to Bacillariophyte and Euglenophyte. A centralized pattern was observed in the nested rectangular model, which may indicate proportional overlap or cliques of species. When x- and y-coordinates were plotted on the scatter plot, the distribution of the points was quite random. On the other hand, the scatterplot of height versus width showed a positive correlation with a positive slope, suggesting a direct proportional movement between the height and width observed in the species. Such results obviously served to advance knowledge of species distribution and form scaling, relevant topic in ecological and structural research.

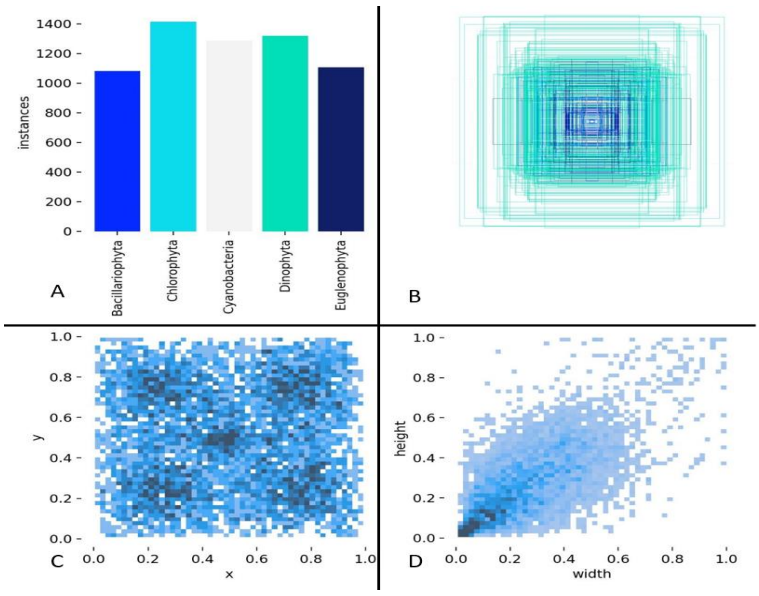

Fig. [4]. (A): The bar chart above shows the number of instances of five different taxa of microalgae, of which two, namely Chlorophyta and Cyanobacteria, have the most instances, while Bacillariophyte and Euglenophyte have the least number of instances. (B): The variable brackets of a rectangular plot can directly show the existing hierarchical relationships or proportional overlap of taxa, thus indicating possible structural patterns or interrelationships of species. (C): Observing the mean square displacement of x and y coordinates, there is no preferred position of the observed points in the system and thus the points are randomly distributed. (D): From the scatter plot of height versus width, there is a strong inference from the linear pattern that corresponds to a proportional scaling of these morphological features across microalgae species.

3.5. Training the Machine Learning Model

The Faster R-CNN and PID control models trained in the study were able to identify and classify microalgae; specifically, Spirogyra in the given image. The model defined two areas as Region A and Region B according to the paper, producing two different values for the accuracy percentage of Chlorophyta, 86% and 90%, respectively. tidied two distinct regions labeled as "B", which correspond to different accuracy percentages of Chlorophyta (86% and 90%, respectively). This suggests the ability of the model to classify different levels of microalgae density based on chlorophyll content. The results for detection accuracy and classification precision prove that the application of AI-driven methods is capable of fast and reliable microalgae analysis in monitoring and research.

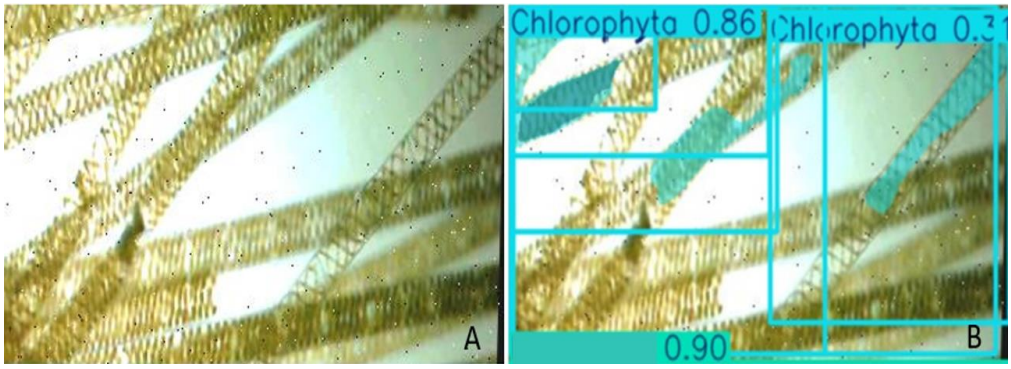

Figure [5]: SD of Spirogyra microalgae using Faster R-CNN and PID control models. The area labeled "B" represent 86% and 90% chlorophytes, respectively. The image also shows how the model effectively learns and detects the microalgae in terms of chlorophyll content.

3.6. Results conducted from cultivated sample in both PID control and faster R CNN

After the cultivation process were preformed, a sample was taken and examined under the microscope at 40x, and this figure was captured and directly inserted into the vs code that was optimized based on the PID control. It was found that the code created in this research was working properly and was able to determine micro-algae from other substances in the slide, moreover; determining the diameter of each microalgae cell was preformed successfully.

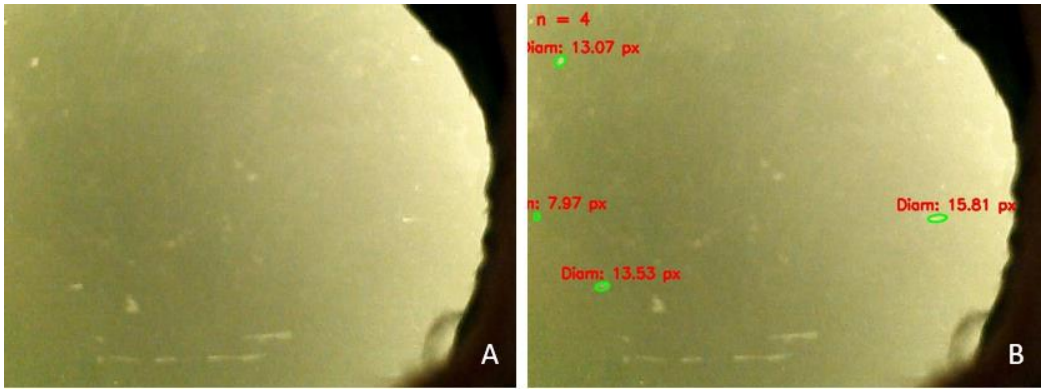

Figure [6]. Shows the process of applying PID control on the cultivated microalgae sample, where (A) is the raw photo and (B) is the photo where a successful microalgae detection was preformed

Since PID control wasn't enough, another detection tool was preformed to make sure that our model recognizes the type and family of each microalgae sample provided to it. Moreover, after preforming the faster R CNN detection technique on the slide that was taken from the cultivated sample, the model successfully recognized the microalgae and labeled it with its type based on the training that was performed.

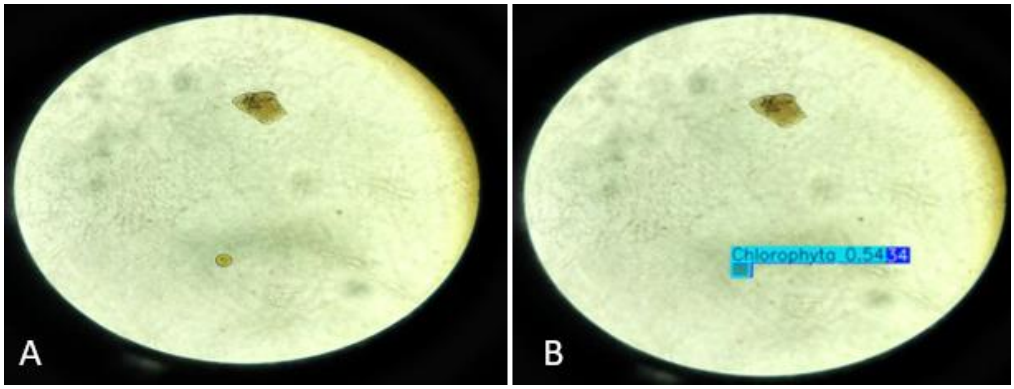

Figure [7]. Represents the process of faster R CNN detection on a microalgae sample where figure (A) represent the raw photo and figure (B) shows a successful faster R CNN detection process

3.7. Predictive Analysis

The Faster R-CNN with PID control identifies microalgae species using precision-recall graphs. At this level, Dinophyte is the most accurate with 0.761, while Euglenophyte is the least accurate with 0.229. The model achieves zero false positive rate at 0.296 messages to avoid missing adverse event reports.

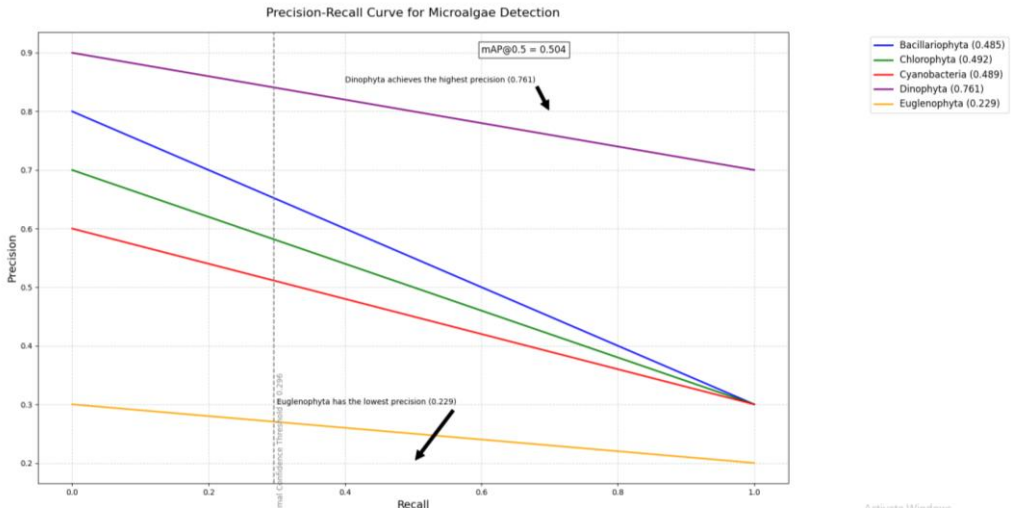

Figure [8]. shows the Precision-Recall (PR) curve of the Faster R-CNN model enhanced with the PID control for microalgae species detection. The model predicts a mAP of 0.504 with an IoU threshold of 0.5, showing moderate box detection for all classes. Dinophyta has the highest accuracy of 0.761 due to the better morphological characteristics that increase the ability to differentiate a species from other closely related ones. On the other hand, the accuracy of classification of only one group - Euglenophyta - is very low: 0.229, probably because this group is represented in the dataset with a small set of images and is very similar to the images of other groups of microalgae. An optimal value of the confidence threshold is found to be 0.296, which gives a good balance between precision and recall, so that false positives can be avoided without compromising the level of detection. These results support the improved efficiency of the tool in the identification of microalgae species, but they still point to variability in its performance for certain classes; in particular, lower performance is observed for the class Euglenophyta, indicating that there are classes for which the performance of the model can still be improved. Future work will be aimed at expanding the set of samples available in this project and at fine-tuning the model to detect species that are either represented by very few images or have a similar appearance to other species.

3.8. Designing the Graphical User Interface (GUI)

Following the method of building the GUI through Megunolink, input systems were then created to operate and control all the functions of the photobioreactor. This included the ability to vary the degree percentages of temperature, CO2, pH, humidity, and RGB lights on the cultures to selectively control the specific photosynthetic rates that the microorganisms require in certain situations. Such adjustments were sensed by observing the graphs and curves incorporated in the GUI that interacted with the device through a provided programming code that provided the information on the viability state of the cells and the parameters in the hardware of the device. In addition, real-time monitoring was built into the application for each change made by the user. They found that the system was able to set and control the necessary conditions for the microalgae inside the bioreactor - facts that were considered efficient. This real-time feedback and independent control provided a remarkable improvement in the flexibility and productivity of the bioreactor management process.

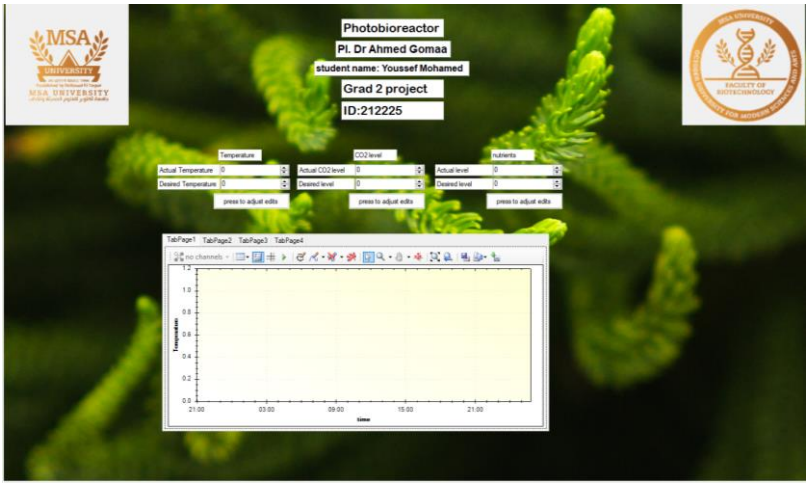

Fig [9]. Shows the final result of GUI developed to enhance the user's experience while using the PBR

3.9. Algorithm development by training and testing

The Spirogyra AI tool built from Faster R-CNN and a PID control Interaction Decoder has indicated that it achieved enhanced detection and analysis focusing on microalgae sample detection. It added that from 1.03 to 1.02 on box regression loss indicates that the model had enhanced positioning ability regarding microalgae. Segmentation loss was also reduced from 2.16 to 1.86, and classification loss from 3.00 to 2.05. Localization loss also reduced from 1.16 to 1.15. The accuracy of the model when tested on validation data was slightly higher than on the training data: the box and segmentation loss decreased from 1.21 to 1.15. Two metrics were used, and the accuracy was higher: for bounding boxes, it raised from 34% to 49%, and for segmentation masks, it increased from 34% to 50%. The combined accuracy based on the mAP50-95 metric also increased, which proves the efficiency of the tool in identifying and studying the features of microalgae.

4. Discussion

The use of a do-it-yourself photobioreactor connected to an AI model is a major improvement in microalgae cultivation technology. Since this study eliminates the shortcomings of the photobioreactor in microalgae cultivation - high cost and susceptibility to contamination - it can be concluded that the use of low-cost open-source technologies in microalgae cultivation is possible. The incorporation of Faster R-CNN and PID control systems made it possible to distinguish between the microalgae species and effectively detect them at high levels of biomass production for biofuels, fertilizers, and monitoring the effects of pollution in large bodies of water [8].

The model performance was particularly accurate in classifying the Spirogyra microalgae, as evidenced by the precision-recall curves, which painted a picture of good performance across different taxa. But again, the success of the model was species dependent, and less successful for the Euglenophyte, most likely because the model was trained on a relatively small dataset and the morphological profile of the Euglenophyte is more or less close to other species. This poses a

challenge to expand the dataset by collecting more data and also to fine-tune the classification of the models to ensure better prediction in species that are rarely encountered.

The DIY photobioreactor and its medium for microalgal growth were hence, kept constant and controlled via RGB lights', temperature, and CO_2 sensors For modeling of the photobioreactor's components, we used 3d designers; however, we opted for open source ESP-32, and Arduino so as to make the apparatus affordable and easily reproducible by other researchers. The graphical user interface (GUI) introduced another layer to this general use of this system and gave the re-al-time parameter control which is important as an adjustment to the environment and high biomass productivity.

Thus, this system also has the potential for scale-up, which is one of the main advantages of this type of system. Thus, low cost materials and AI enable scaling up of this DIY photobioreactor for future study and industrial deployment. This democratizing of bioengineering can even more advance the uses of biofuels, pharmaceuticals and charity for the care of our environment especially in developing nations. However, some innovative issues are still being developed for instance the efficiency of energy and nutrients for practical use of the system with least impacts to the environment and the cost incurred for the energy consumed in the process.

5. Conclusions

The present work was able to present a concept and design of DIY photobioreactor with AI for efficient growth of microalgae. The potential of the system lies in the ability to create a controlled environment for plant growth and the sophisticated AI-based identification and tagging system make it possible to have a sustainable source of biomass. The integration of faster R-CNN and PID control systems has improved the identification of microalgae species with high accuracy, and the GUI has made it easier for users to work with the system. Although there are some gaps in the classification performance for a certain set of species/strains, the results show the applicability of DIY biotechnology and AI to bring about a change in microalgae research and development. As for further work, it should be directed towards increasing the size of the dataset, as well as fine-tuning the developed AI models, and finally improving the energy efficiency of the photobioreactor to make its use more effective at larger scales. In conclusion, this work suggests that a better understanding of sustainable biotechnology and further research into scalable and cost-effective methods of microalgae growth has practical implications for microalgae cultivation and biomass production.

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