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Detection of algae in a Hydroponics Using CNN and YOLOv8 Algorithms

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ABSTRACT: Hydroponics offers sustainable cultivation, but algae growth can hinder its efficiency by depleting nutrients and disrupting oxygen levels. This study introduces an integrated solution for detecting algae in hydroponic systems using a combination of temperature sensors, smoke sensors, and live camera analytics. The temperature sensor monitors water and environmental conditions conducive to algae growth, while the smoke sensor detects changes in air quality that may indicate hazardous factors promoting algae. A live camera feed, analyzed with computer vision algorithms, identifies algae presence with high accuracy, ensuring real-time monitoring and timely intervention. The proposed system enhances algae detection precision and system automation, improving crop health and productivity. Initial results demonstrate the system's ability to reliably detect algae, making it a scalable and effective tool for maintaining optimal hydroponic conditions. Future enhancements will focus on refining detection accuracy and extending system capabilities for broader applications in controlled agriculture.

I. INTRODUCTION

Hydroponics, a sustainable and efficient method of soil-free cultivation, offers significant benefits for resource conservation and crop productivity. However, algae growth in hydroponic systems presents a critical challenge, as it depletes essential nutrients, reduces oxygen levels, and disrupts plant health. To address this issue, this study introduces an integrated detection system combining temperature sensors, smoke sensors, and live camera analytics powered by computer vision algorithms. The temperature sensors monitor environmental and water conditions conducive to algae formation, while the smoke sensors detect air quality changes that might indicate hazardous factors. A live camera feed analyzes visual algae growth in real-time, ensuring prompt intervention. Initial results demonstrate the system's effectiveness and scalability, marking a significant step toward optimizing hydroponic system efficiency and sustainability.

II. EXPERIMENTAL FIELD

2.1.1. Hydroponics System and Planting

Growing in a hydroponic system requires a series of careful steps to ensure optimal growth and health of the plants. The process begins with seed germination in inert non-biological materials such as rock wool or cocoa coir, which provide support and are easily transferred to a hydroponic system. When seedlings develop a complex root system and few true leaves only some are transferred to a hydroponic system. Ensure that nutrient inputs, which must be carefully balanced with the essential elements, are constantly monitored and adjusted for optimum pH and electrical conductivity (EC) levels. In addition, supplemental lighting, usually from energy-efficient LED grow lamps, to mimic natural sunlight and support photosynthesis primarily indoors -Or Provided in bright areas there is little Routine maintenance, including system cleaning, nutrient solution adjustments, and monitoring plant health for disease or nutrient deficiencies signal, is critical for proper functioning of the system and maintaining plant welfare. Improves yield and resource utilization.



2.1.1.1 Hydroponics at Outdoor



2.1.1.2 Hydroponics at Indoor

2.1.2. Camera Systems

The effectiveness of algae detection in hydroponic systems depends significantly on the **camera system** used for image acquisition. High-quality, well-positioned cameras ensure accurate data collection, enabling YOLOv8 and CNN to perform optimally.

1. Camera Selection Criteria

Choosing the right camera involves considering several key factors:

- **Resolution:** High-resolution cameras (e.g., 1080p, 4K) capture fine details in algae growth.
- **Frame Rate:** A minimum of **30 FPS** ensures smooth real-time monitoring.
- **Lens Type:** Wide-angle lenses cover larger areas, while macro lenses capture finer details.
- **Infrared (IR) & Multispectral Imaging:** Helps detect algae growth not visible in normal lighting.
- **Waterproof & Durability:** Cameras should be resistant to moisture and harsh hydroponic environments.

2. Camera Placement & Setup

Proper positioning of cameras is essential for optimal coverage and detection accuracy.

- **Overhead Cameras:** Mounted on top to monitor large hydroponic beds.
- **Side-Angle Cameras:** Placed at different angles to detect algae on tank walls and pipes.
- **Underwater Cameras:** Used for submerged systems to detect algae growth below the water surface.
- **Automated Camera Movement:** Pan-tilt-zoom (PTZ) cameras can scan large areas dynamically.

3. Image Capture & Preprocessing

Before being fed into YOLOv8 and CNN, images undergo preprocessing to enhance detection accuracy:

- **Noise Reduction:** Gaussian blur or median filtering removes unwanted noise.
- **Contrast Enhancement:** Histogram equalization improves algae visibility.
- **Edge Detection:** Sobel or Canny edge detection highlights algae contours.
- **Normalization:** Adjusts brightness and sharpness for consistent results.

4. Integration with Detection System

- **Cameras continuously capture images/video** of the hydroponic system.
- **Images are processed in real-time** using a local processing unit (e.g., Raspberry Pi, Jetson Nano) or cloud-based system.
- **YOLOv8 detects algae presence**, while **CNN classifies severity levels** based on camera feed.
- **Detected areas are highlighted** in a dashboard for real-time monitoring and alerts.

2.2. Image Data Acquisition

Image data acquisition in hydroponics for algae detection using CNN and YOLOv8 is a simple but important process that lays the foundation for an effective detection system. The first step is to establish a robust image capture system in the hydroponic environment. High-resolution cameras are strategically placed to cover different parts of the hydroponic system, ensuring full coverage. These cameras need to be positioned to capture images in different lighting conditions, as algae can grow in well-lit, shaded areas.

The next step is to gather a diverse set of images. During this time periodic photographs of the water system are taken. It is important to collect images showing different stages of algae growth, from early to advanced stages, as well as clean algae-free areas, this diversity ensures that the trained model can accurately detect algae at all stages in and under different circumstances.

Once the images are saved, the next step is annotation. Each image is carefully labelled to indicate the presence or absence of algae. This is usually done with annotation tools such as Label Image or Robo flow, where bounding boxes are drawn around the algae in the images. Accurate specification is important because it directly affects the performance of the trained model.

Data enhancement techniques such as transformation, scaling, and flipping are then applied to the labelled images to automatically increase the size of the data set. This helps improve the robustness of the model by providing more training samples with the world on the self-conditions they imagine.

2.3. Image/Data Pre-processing

2.3.1. Image Annotation

Image annotation is a critical step in developing an effective system for detecting algae in hydroponic environments using CNN and YOLOv8 algorithms. This process involves labelling images of the hydroponic system to highlight the presence and location of algae, thereby creating a dataset that can be used to train and evaluate the deep learning models. The first step in image annotation is to gather a diverse collection of images from the hydroponic system. These images should be captured under various conditions, including different lighting and angles, to ensure the dataset is comprehensive. Using high-resolution cameras can enhance the quality of the images, making the annotation process more precise and reliable. Once the images are collected, they are uploaded to an annotation tool. Several user-friendly tools are available, such as Label Image, Robo flow, and VGG Image Annotator (VIA), which allow users to manually draw bounding boxes around the regions where algae are present. The annotation process involves drawing precise bounding boxes around algae spots and assigning appropriate labels. For instance, each bounding box is labelled as "algae," distinguishing it from other elements in the hydroponic setup. This manual annotation ensures that the dataset is accurate and provides clear examples for the neural networks to learn from. It's important to annotate a diverse set of images, including those with varying sizes and densities of algae, to improve the model's ability to generalize and detect algae in different scenarios.

2.3.2. Image Augmentation

Image augmentation is a pivotal step in preparing image datasets for training CNN and YOLOv8 models to detect algae in hydroponic systems. This process involves applying a variety of transformations to existing images, thereby expanding the dataset and enhancing the model's ability to generalize across different conditions.

To begin with, augmentation techniques such as rotation, scaling, and flipping are commonly used to artificially increase the diversity of the dataset. By rotating images at different angles, the model learns to recognize algae from multiple viewpoints, mimicking real-world scenarios where algae may appear at different orientations within the hydroponic environment.

Scaling involves resizing images to different dimensions, both enlarging and shrinking them. Flipping horizontally or vertically mirrors images, providing additional variations that help the model learn from mirrored instances of algae growth. Moreover, introducing random crops from original images helps simulate scenarios where algae might occupy only a portion of the captured frame. This augmentation method enhances the model's ability to accurately detect algae in partially visible or obscured conditions within the hydroponic environment.

Adding noise to images through techniques like Gaussian blur or colour jittering can simulate poor lighting conditions or camera artifacts, ensuring the model remains robust against such challenges. These transformations collectively contribute to a more resilient model that can effectively detect algae across diverse environmental conditions and image qualities. This augmentation-driven approach not only improves detection accuracy but also supports sustainable agriculture practices by enabling early intervention and efficient management of hydroponic systems.

2.3.3. Datasets

The "Algae Detection Dataset" the Roboflow universe includes images with 1,048 marked images specifically designed to detect algae in different environments. The dataset contains annotated images with the boundary box, which is suitable for the training machine learning model to identify algae. It supports many formats such as Yolo, Coco and Tensor flow, which provides flexibility in model development. The dataset is publicly available below the 4.0 license under CC, making it available for research and commercial use. This dataset is useful for applications in environmental monitoring of hydroponic systems, evaluation of water quality and algae detection applications.

<https://universe.roboflow.com/new-workspace-tccht/algadedetection-skcsw>

2.4. Detection and Classification Methods and Tools

2.4.1. Model Training Procedure (flowchart)

Original Image: The original image process begins by achieving the original dataset, which acts as a basis for later stages.

Image Annotation: The image in images annotation in manual or semi-automatic labeling of images ensures that the data is accurately designed for monitored learning.

Image Conversion: Image conversion images are converted to a format compatible with YOLOv8 models, which standardize dimensions and data types.

Dataset Creation: Dataset creation is organized a curated dataset, including annotated images in structured directories for training and verification.

Training Dataset: The training data set data set is divided into multiple sets (training, verification and possibly testing) to ensure a strong model assessment of the dataset.

Image Augmentation: Image enlargement techniques such as rotation, scaling and flipping are used to increase data set variability and improve model generalization.

Model Training: Model training is trained using the YOLOv8 model prepared dataset. Exercise involves reducing losses and adapting the model parameters to achieve accurate predictions.

Detection Model: Detection model Trained YOLOv8 models are distributed for Real World Detection Tasks and get accurate and effective results.



2.4.2. Tools

Software Tools

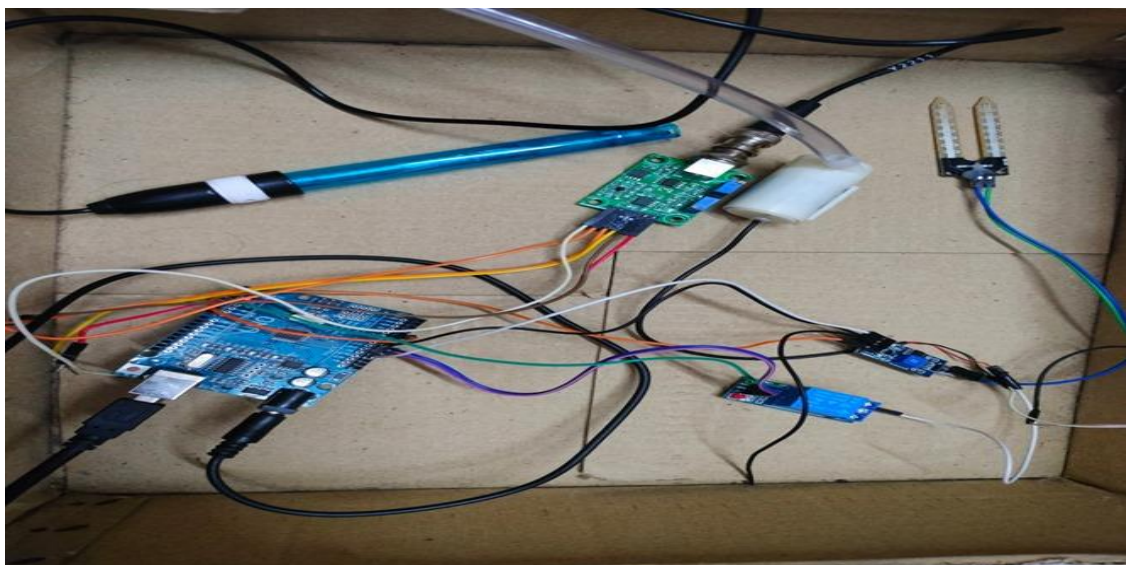
- YOLOv8 (Ultralytics Yolo): Deep Learning Model for Object Detection and Classification.
- OpenCV: Image processing and computer vision library to analyze algae development.
- Streamlit: Used to create an interactive web application for detection.
- PIL(pillow): Handle the image processing tasks like reading and viewing pictures.
- NumPy : The deep learning model converts images for input to array format.

Hardware Tools

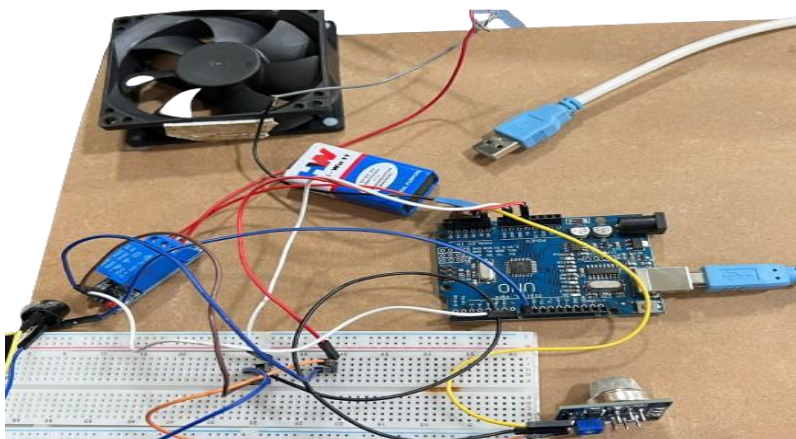
- Arduino uno
- Esp32
- Ph sensor
- Temp sensor
- Smoke Sensor
- TDS Sensor
- 12V 0.70A 8025 8CM 2-wire cooling fan
- Bread board
- Jumper wire
- Relay Module FL-37F-5
- OLED DISPLAY



2.4.2.1 Hydroponic Seedlings in Clay Pebble Media



2.4.2.2 Arduino Sensor Setup



Pin Configuration :

Connect these sensors and components to ESP32 pins:

OLED Display:

- VCC - 3.3V
- GND - GND
- SCL - GPIO 22 (default ESP32 I2C SCL)
- SDA - GPIO 21 (default ESP32 I2C SDA)

DHT Sensor:

- VCC - 3.3V
- GND - GND
- Signal Pin - GPIO 15

pH Sensor:

- Signal Pin - GPIO 34 (Analog input)

MQ-2 Smoke Sensor:

- Signal Pin - GPIO 35 (Analog input)

Buzzer:

- Positive - GPIO 13
- Negative - GND

Relay Module for Fan:

- Signal Pin - GPIO 12
- VCC - 5V (relay power)
- GND - GND

III. METHODOLOGY**1. Data collection and pre -processing**

Data set collection: Images of hydroponic systems with different levels of algae development are collected using high -resolution cameras.

Annotation: Dataset is marked using a boundary box to highlight the appearance of algae for training Yolo v8 training.

Computer text: Techniques such as rotation, flipping, contrast adjustment and noise additions increase the strength of the model.

2. YOLOv8 to detect algae

Model choice: YOLOv8 is chosen for the abilities to detect its real -time object, which provides high accuracy and efficiency.

Training process: The model is trained on Annotate images using Transfer Learning to improve performance with limited data.

Detection pipeline: Input image is treated through YOLO v8, which detects algae areas and provides trust points.

3. CNN for classification and severity estimate

Functional recovery: An enhancement network (CNN) detected the main functions of the algae update.

Classification: CNN classifies the development of algae to different severity levels (eg low, medium, high).

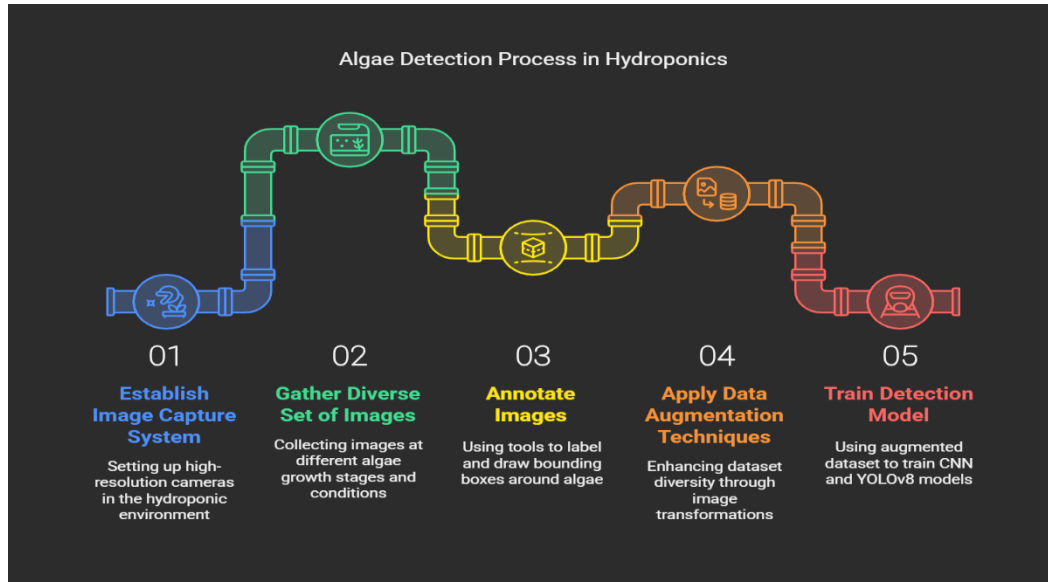
Model adaptation: Techniques such as batch normalization, dropout and hyperparameter setting increase the CNN accuracy.

4. Integration with hydroponic system

Automatic monitoring: Trained models are distributed on edge units (eg Raspberry Pi, Jetson Nano) for real -time monitoring.

Alert Mechanism: When algae exceeds the predetermined limit, the notification is sent to farmers via dashboard or mobile application.

Continuous learning: The system is updated with new data from time to time to improve detection and classification accuracy.



IV. ALGORITHMS

1. YOLOv8 – Real-Time Object Detection

YOLOv8 (You Only Look Once, Version 8) is a deep learning-based object detection algorithm used to detect algae in hydroponic systems efficiently.

Key Features:

- **Single-stage detection:** YOLOv8 processes the entire image in one pass, making it faster than two-stage detectors like Faster R-CNN.
- **Anchor-free design:** Unlike previous YOLO versions, YOLOv8 eliminates the need for anchor boxes, improving detection accuracy for irregular-shaped objects like algae.
- **Improved backbone (CSPDarknet):** Uses a lightweight yet powerful convolutional backbone for feature extraction.
- **Non-Maximum Suppression (NMS):** Removes redundant bounding boxes to refine detections.
- **Output:** Provides bounding boxes around algae growth along with confidence scores.

Detection Workflow:

1. **Input Image Processing:** Images are resized and normalized for model compatibility.
2. **Feature Extraction:** YOLOv8's CSPDarknet backbone extracts essential features.
3. **Object Localization:** The network predicts bounding boxes, class probabilities, and confidence scores.
4. **Filtering Predictions:** NMS is applied to eliminate duplicate detections.
5. **Final Output:** Algae regions are highlighted with bounding boxes and confidence levels.

2. CNN (Convolutional Neural Network) – Classification

A **Convolutional Neural Network (CNN)** is an intensive teaching model designed for the processing and analysis of visual data, such as images and videos. In this way, it copies the human brain automatically processes the visual information by detecting patterns, edges and functions. CNN includes several layers, including fixed layers for extraction of functions, merging layers for relief reduction and perfectly associated teams for classification. They are widely used in applications such as image recognition, object detection, medical imaging and autonomous systems due to their high accuracy and efficiency in handling complex visual functions.

Key Features:

- **Hierarchical Feature Extraction:** CNN automatically learns important features like colour, texture, and size variations in algae.

- **Pooling Layers:** Reduce spatial dimensions while retaining essential information, improving computational efficiency.
- **Fully Connected Layers:** Generate final classification predictions based on extracted features.

Activation Functions:

- **ReLU (Rectified Linear Unit):** Introduces non-linearity for better feature learning.
- **Softmax:** Converts CNN outputs into probability distributions for multi-class classification.

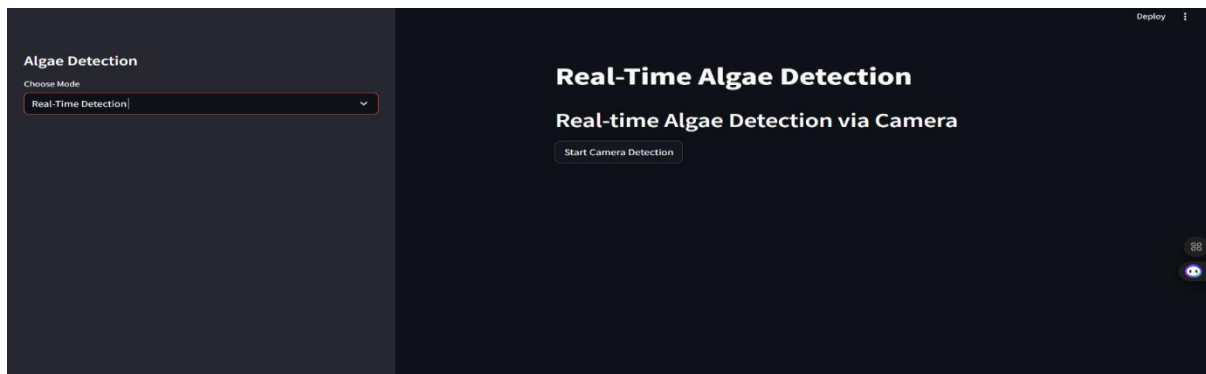
Classification Workflow:

1. **Input Preprocessing:** Cropped algae regions from YOLOv8 are resized and normalized.
2. **Feature Extraction:** Convolutional layers identify key algae characteristics.
3. **Pooling & Flattening:** Extracted features are downsampled and converted into a vector.
4. **Classification Layer:** The fully connected layers classify the algae into different severity levels (e.g., Low, Medium, High).
5. **Final Output:** The severity category is assigned with a confidence score.

V. RESULTS, ANALYSIS AND DISCUSSIONS

5.1 Results

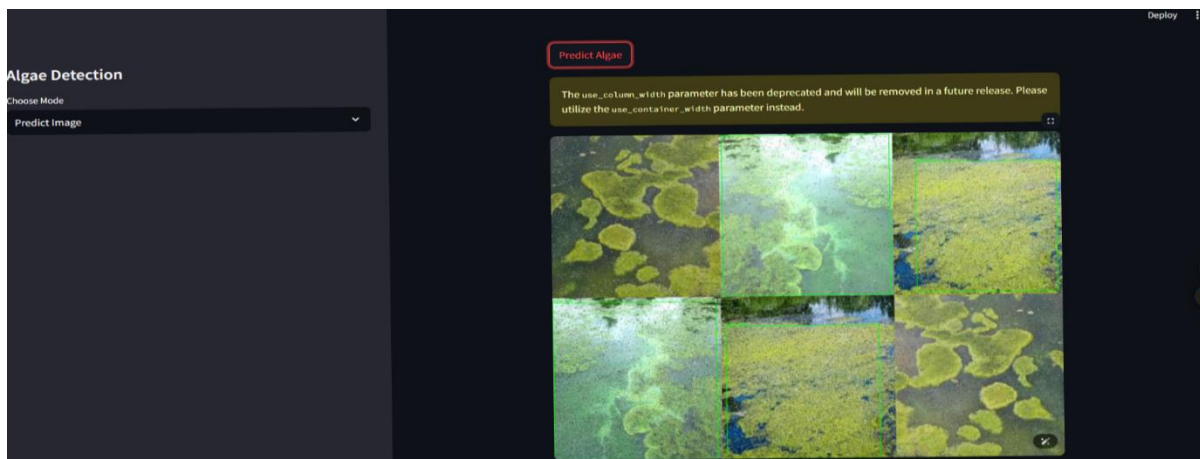
5.1.1. Pre-Model Data visualization



5.1.1.1. Real-Time Algae Detection

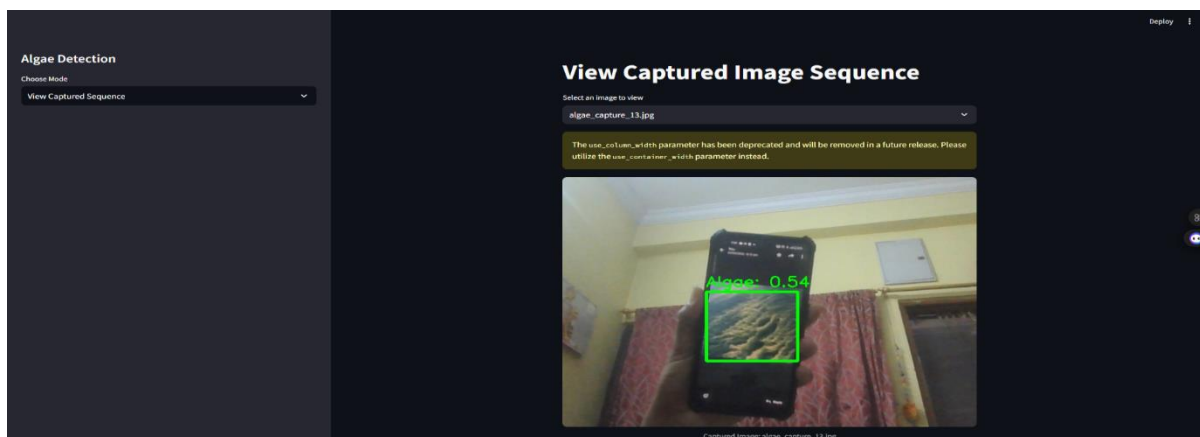


5.1.1.2 Interface of uploading an Image for Algae Detection



5.1.1.3 Finding Algae in given datasets

5.2 Analysis



5.2.1 predicting algae with accuracy value-0.54



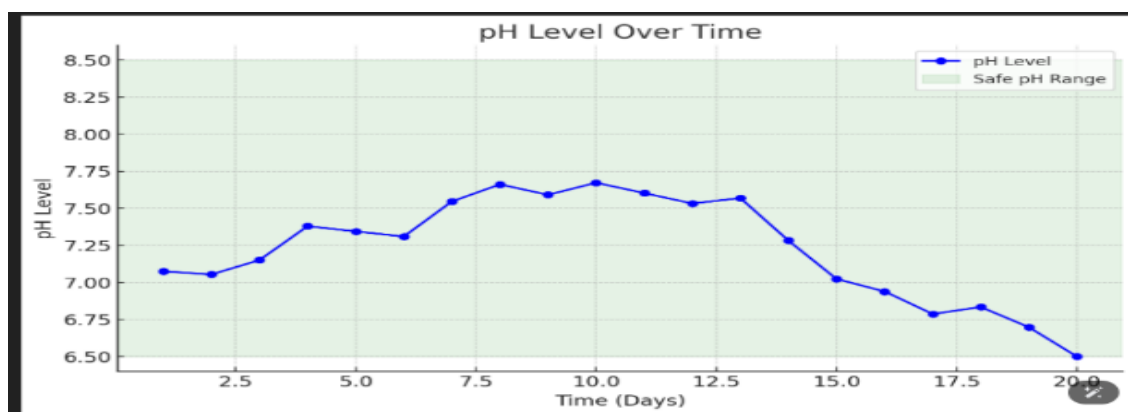
5.2.2 predicting algae with accuracy value-0.50

5.2.3 predicting algae with accuracy value-0.74

The interface shows an algae detection system that analyzes an image, which appears as "algae: 0.54" with an explanation of a detection. This value represents an example, but the system's capacity is expanded beyond the witty threshold, which provides a dynamic area. By monitoring the belief in constant separate detection, the equipment shows strong adaptability by assessing the ALGA levels under different environmental conditions. This versatility increases its accuracy and reliability in organic management efforts.

5.3 Discussions

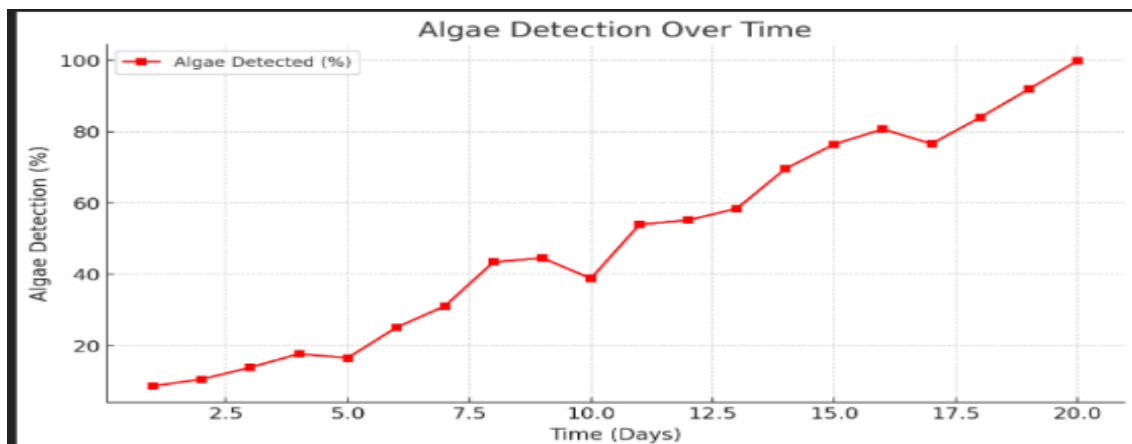
Time (Days)	pH Level
0.0	7.10
2.5	7.10
5.0	7.35
7.5	7.50
10.0	7.65
12.5	7.75
15.0	7.50
17.5	7.00
20.0	6.75



5.3.1 Ph Level Over Time

The above graph shows the pH level fluctuations during the 20-day period, highlighting the effect on water quality. It begins around 7.25, the peaks from 10 to 7.75 days, sinking by 6.75 days. This analysis is important for understanding environmental variations and maintaining conditions within a safe pH area for aquatic organic systems.

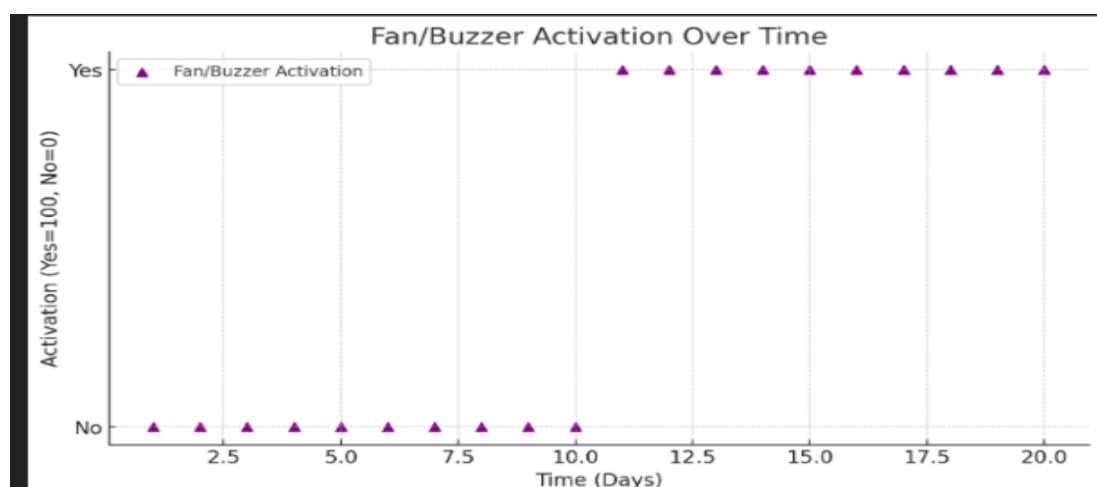
Time (Days)	Algae Detection (%)
0.0	0
2.5	20
5.0	35
7.5	50
10.0	65
12.5	75
15.0	70
17.5	60
20.0	55



5.3.2 Algae Detection Over Time

The above graph reflects a percentage increase in algae detection over a period of 20-day. The trend reflects a stable increase, indicating a frequent increase in the appearance of algae. This data is important for analyzing algae spread patterns, which can provide insight into environmental factors that affect water quality. Such findings are effectively important for the monitoring and management of aquatic ecosystems.

Time (Days)	Fan/Buzzer Activation (Yes=100, No=0)
0.0	100
2.5	0
5.0	0
7.5	100
10.0	100
12.5	100
15.0	100
17.5	100
20.0	100

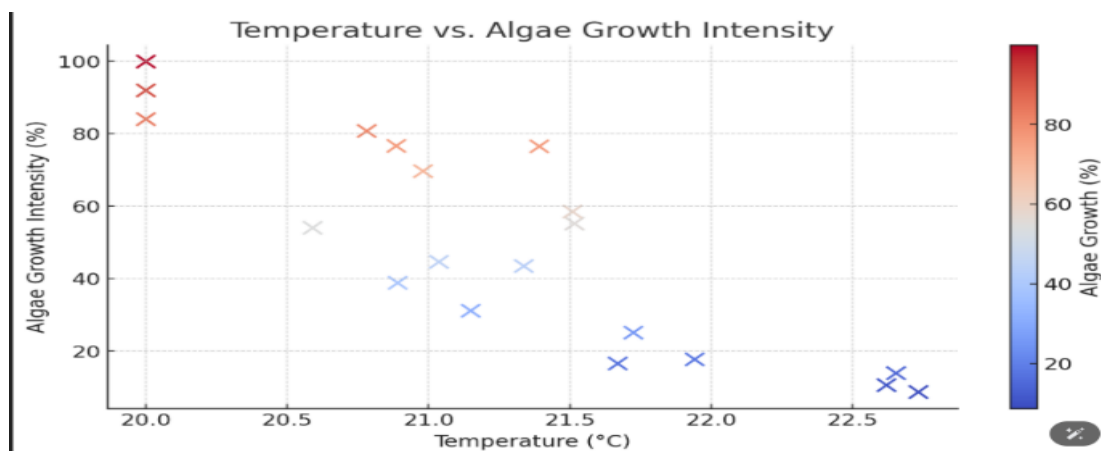


5.3.3 Fan/Buzzer Activation Over Time

The graph shows the activation pattern of the 20 -day fan or the activation pattern of Bajer, which has activism characterized by the purple triangle. Events occur occasionally, the frequency increases after a 10-day mark. This

pattern can improve the expanded environmental trigger or need to increase the requirements for conditions, which require activation, provides insight into algae detection and system optimization in the response system.

Temperature (°C)	Algae Growth Intensity (%)	Observation
20.0	~100	High algae growth at lower temperatures.
21.0	~70	Moderate algae growth as temperature rises.
22.0	~30	Significant decline in algae growth.
22.5	~10	Minimal algae growth at higher temperatures.



5.3.4 Temperature Vs Algae Growth Intensity

The plot of spread shows the ratio of temperature (°C) and intensity of algae growth (%), which shows a declining trend growing as the temperature rises from 20.0 °C to 22.5 °C-colored data points, blue to red infections, emphasizes visually this correlation. This analysis illuminates the significant effect of temperature on algae spread, which provides valuable insight into environmental management strategies.

Timestamp	Temperature (°C)	pH Level	Smoke Detection (PPM)	Fan Status
2025-03-10 10:00	25	6.5	80	OFF
2025-03-10 10:10	27	6.8	95	OFF
2025-03-10 10:20	30	7.0	105	ON
2025-03-10 10:30	29	6.9	120	ON
2025-03-10 10:40	28	6.7	90	OFF

5.3.5 Sensor Readings and Algae Detection Trends

The analysis of the dataset reveals a dynamic difference between environmental conditions and automated control systems. The temperature and pH remained within the optimal categories, demonstrating stable conditions. The smoking level triggers the fan, which effectively controlled the air quality by responding to the growing concentrations. This shows the efficiency of integrated systems to maintain an ideal environment, especially for applications such as alpine detection in hydroponics.

VI. CONCLUSION

The integration of a hydroponic system with superior algae detection techniques using Convolutional Neural Networks (CNN) and YOLOv8, paired with hardware components like smoke, temperature, and pH sensors, along ESP32 and Arduino Uno, establishes a complete answer for green water first-rate monitoring. This system leverages the photograph reputation skills of CNN and YOLOv8 for real-time detection and type of algal species, making sure well timed intervention against harmful algal blooms. The inclusion of environmental sensors gives vital records on factors influencing algae increase, at the same time as ESP32 and Arduino Uno facilitate seamless data collection and IoT-based totally faraway tracking. Such a setup now not only complements sustainability in hydroponic practices however also contributes extensively to aquaculture and water useful resource control by making sure healthier aquatic ecosystems.

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