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AI-Powered Drone and Harvester System for Aquatic Ecosystem Restoration

Palani Raja T. Sathappan V, Shibie R M , Subeshan M, Valliappan V

***Abstract*—** Invasive aquatic weeds, such as water hyacinth, threatening the health of aquatic ecosystems by depleting oxygen levels, obstructing sunlight, and disrupting water flow, leading to declines in biodiversity, economic losses for local industries, and increased public health risks. The study presents an innovative system that integrates AI-driven drone technology with automated harvesting to manage aquatic weed infestations efficiently. Utilizing YOLOv8 for real-time object detection, Python Flask for seamless data processing, and Google Colab with the Ultralytics framework for model development, the system enables precise monitoring and targeted weed removal.

***Keywords*—** Invasive aquatic weeds, AI-driven drone technology etc

I. INTRODUCTION

Aquatic ecosystems are vital for maintaining ecological balance, supporting diverse species, and providing resources for human activities such as fishing, irrigation, and recreation. However, the proliferation of invasive aquatic weeds, particularly water hyacinth (Eichhornia crassipes), has become a global concern. These weeds form dense mats on water surfaces, reducing dissolved oxygen levels, blocking sunlight penetration, and impeding water flow. The resulting impacts include declining fish populations, disrupted irrigation systems, and the creation of stagnant water pools that serve as breeding grounds for disease-carrying mosquitoes, such as transmitting malaria and dengue. In water bodies are critical for fishing and agriculture, these infestations have led to significant economic losses, with local communities reporting up to a 40% reduction in fish yields and irrigation efficiency. Traditional weed management methods, such as manual removal, mechanical harvesting, and chemical treatments, have significant drawbacks. Manual removal is labor-intensive, requiring large teams to clear even small areas, and is often infeasible for large-scale infestations. Mechanical harvesters, while faster, frequently cause collateral damage to native vegetation and aquatic habitats, exacerbating ecological imbalances. Chemical treatments, such as herbicides, are effective but introduce pollutants into the water, harming non-target species and posing risks to human health through bioaccumulation. These challenges underscore the need for a more efficient, sustainable, and environmentally friendly approach to aquatic weed management.

Palani Raja T , Assistant Professor, Knowledge institute of Technology, Salem, Tamilnadu, India .
Athappan V, Shibie R M , Subeshan M, Valliappan V , UG Scholar , Knowledge institute of Technology, Salem, Tamilnadu, India .

II. LITERATURE REVIEW

The application of technology in aquatic weed management has gained significant attention in recent years, with studies exploring drone surveillance, AI-driven analytics, and automated harvesting systems. Below, it synthesizes key findings from the literature to provide context for research and identify gaps between system addresses.

1) Kumar and Rao (2020) investigated the use of drones equipped with multispectral cameras to map aquatic vegetation in wetlands. Their study demonstrated that drones could cover large areas in a fraction of the time required for manual surveys, achieving a mapping accuracy of 88%. However, the high cost of drone equipment and the need for specialized skills to interpret multispectral data were identified as barriers to widespread adoption, particularly in resource-constrained regions.

2) Patel et al. (2021) developed a semi-autonomous robotic boat for aquatic weed harvesting, using basic image recognition to identify and remove invasive weeds. The system reduced manual labor by 50% and improved removal precision compared to traditional mechanical harvesters. However, it faced challenges in scalability, as the boat's navigation system struggled in complex water bodies with varying depths and underwater obstacles. Additionally, the image recognition model lacked robustness in diverse lighting conditions, limiting its effectiveness during early morning or late afternoon operations.

3) Gupta (2023) explored the role of AI in predicting aquatic weed growth, using machine learning models to analyze historical data on environmental factors such as water temperature, pH, and nutrient levels. The model achieved a prediction accuracy of 85%, enabling proactive management strategies to prevent infestations. However, its performance was heavily dependent on the availability of high-quality data, with incomplete or noisy datasets leading to inaccurate predictions, highlighting the need for robust data collection methods.

4) Other studies have focused on the environmental impact of weed management techniques. Rao et al. (2019) examined the ecological consequences of mechanical harvesters, noting their tendency to uproot native plants and disturb aquatic habitats, which can lead to long-term ecosystem degradation. Similarly, Nair (2022) evaluated the use of chemical treatments, emphasizing their effectiveness in killing weeds but highlighting the long-term harm to water quality and aquatic life due to chemical runoff and bioaccumulation.

5) While these studies provide valuable insights, they often focus on isolated aspects of weed management such as monitoring, prediction, or removal—without integrating them into a cohesive system. The research addresses the gap by combining dronebased surveillance, AI-driven detection using YOLOv8, and automated harvesting into a unified framework. By leveraging Python Flask for real-time data processing and Google Colab for efficient model development, we aim to overcome the scalability, cost, and usability challenges identified in prior work, while ensuring minimal environmental impact.

A. Existing Methods

Several methods have been employed to manage aquatic weed infestations, each with distinct advantages and limitations, providing a foundation for the development of our proposed system. Below, we outline the primary existing approaches and their challenges:

1. Manual-Removal

Manual removal involves labourers physically extracting weeds from water bodies using tools like rakes, nets, or boats. This method is widely used in small-scale settings due to its low equipment cost and minimal environmental footprint. However, it is highly labour-intensive and time-consuming, with teams of 10–15 workers often requiring days to clear a single hectare, achieving only 50–60% weed removal efficiency. In large water bodies, such as lakes or rivers, manual removal becomes impractical, and regrowth occurs rapidly without continuous effort, rendering it unsustainable for widespread application.

2. Mechanical Harvesting

Mechanical harvesters, such as boat-mounted cutters or conveyor systems, offer a faster alternative, capable of clearing up to 1–2 hectares per day depending on the equipment. Studies, such as Rao et al. (2019), report removal efficiencies of 70– 80%, significantly higher than manual methods. However, these systems lack precision, frequently uprooting native plants and disturbing aquatic habitats, with collateral damage affecting up to 20% of non-target vegetation. Additionally, high operational costs (e.g., $800–$1,000 per hectare) and the need for frequent maintenance limit their feasibility in resourceconstrained regions.

3. Chemical Treatments

Herbicides, such as glyphosate and 2,4-D, are applied to kill aquatic weeds rapidly, often achieving near-100% clearance within days. Nair (2022) notes their effectiveness in controlling large infestations, particularly in static water bodies. However, chemical runoff pollutes water, reducing dissolved oxygen levels and causing bioaccumulation in fish and other organisms, with long-term consequences for biodiversity and human health. Regulatory restrictions in many regions further limit their use, and costs can exceed $500 per hectare, including application and monitoring expenses.

4. Biological Control

Biological methods involve introducing natural predators, such as weevils (Neochetina spp.) or fungi, to suppress weed growth. These approaches are environmentally friendly and cost-effective over time, with minimal intervention required post-introduction. However, their slow action—often taking months to years to achieve noticeable results—makes them unsuitable for urgent infestations. Additionally, their efficacy varies with environmental conditions, and unintended ecological impacts, such as predator overpopulation, remain a concern.

5. Emerging Technological Solutions

Recent advancements have explored technology-driven methods, such as drone surveillance and robotic harvesting. Kumar and Rao (2020) demonstrated drones mapping aquatic vegetation with 88% accuracy, though high costs and data interpretation challenges hinder adoption. Patel et al. (2021) developed a semi-autonomous boat with basic image recognition, reducing labour by 50%, but its navigation struggles in complex water bodies. These solutions, while promising, lack integration into a cohesive, scalable system, leaving gaps in real-time detection, precise removal, and environmental sustainability.

B. Problem Statement

Invasive aquatic weeds, such as water hyacinth (Eichhornia crassipes), pose a severe threat to aquatic ecosystems worldwide, disrupting ecological balance, economic stability, and public health. These weeds proliferate rapidly, forming dense mats that deplete dissolved oxygen levels, block sunlight penetration, and impede water flow, resulting in biodiversity loss, reduced fish yields, and compromised irrigation systems. For instance, in heavily infested water bodies, fish populations have declined by up to 40%, and irrigation efficiency has dropped by 30–50%, severely impacting livelihoods in fishing and agricultural communities. Existing weed management techniques—manual removal, mechanical harvesting, and chemical treatments—are plagued by inefficiencies and environmental drawbacks. Manual removal is labor-intensive and impractical for large-scale infestations, often requiring dozens of workers to clear small areas with limited success rates (e.g., 50% weed clearance). Mechanical harvesters, while faster, cause collateral damage to native vegetation and aquatic habitats, with studies reporting up to 20% disruption of non-target species. Chemical treatments introduce pollutants that degrade water quality and harm aquatic life through bioaccumulation, posing long-term risks to ecosystems and human health. These limitations highlight an urgent need for an innovative, sustainable, and scalable solution that can efficiently target invasive weeds while minimizing ecological harm and operational costs. This study addresses this gap by proposing an AI-powered drone and harvester system to restore aquatic ecosystems with precision and efficiency.

III. METHODOLOGY

The system is designed to manage aquatic weed infestations through a multi-stage process, integrating hardware and software components for efficient monitoring, detection, and removal. The methodology is structured into several interconnected phases, each developed with a focus on precision, scalability, and sustainability.

A. System Architecture Diagram

3.1 System Overview

The proposed system consists of three main components: (1) drones for data collection and monitoring, (2) AI pipeline for real-time weed detection a (3) automated harvesters for targeted weed removal. The drones capture high-resolution images and environmental data, which are processed by the AI pipeline to identify weed clusters. The processed data is then transmitted to the harvesters, which execute precise removal operations. A web application built with Python Flask serves as the central hub, managing data flow and providing a user interface for monitoring and control.

3.2 Data Collection

By conducting data collection in a 10-hectare water body, heavily infested with water hyacinth. Drones equipped with high-resolution cameras (12 MP), LIDAR sensors, and environmental sensors were deployed to capture a comprehensive dataset. The drones followed pre-programmed flight paths, ensuring systematic coverage of the water body. Over a two-week period, they collected 6,500 images, each capturing a 10x10 meter area at a resolution of 1280x720 pixels. Environmental sensors recorded metrics such as pH, dissolved oxygen, water temperature, and nutrient levels at 15-minute intervals, resulting in a dataset of 2,500 environmental readings. The drones were equipped with GPS and GNSS modules to geotag each image, enabling precise mapping of weed infestations.

3.3 Data Preprocessing

The collected data underwent extensive preprocessing to ensure compatibility with AI models. Images were resized to 640x640 pixels to match the input requirements of YOLOv8, and noise such as water reflections, cloud shadows, and glare was mitigated using a combination of Gaussian blur, histogram equalization, and adaptive thresholding. To enhance model robustness, By applying data augmentation techniques, including random rotations (0–45 degrees), horizontal and vertical flips, brightness adjustments (±20%), and contrast variations (±15%). Increased the dataset size to 19,500 images, providing a diverse set of training examples to improve the model’s generalization across different environmental conditions. Environmental data was normalized to a 0–1 scale to facilitate integration with the AI models. Missing values, which accounted for 4% of the dataset due to sensor malfunctions, were imputed using a time-series interpolation method based on the Savitzky-Golay filter. Outliers, identified using the interquartile range (IQR) method, were capped to prevent skewing the model’s predictions.

3.4 Model Architecture

The AI pipeline consists of two main models: YOLOv8 for object detection, and a Recurrent Neural Network (RNN) for temporal analysis.

3.4.1 YOLOv8 for Object Detection

YOLOv8, developed by Ultralytics, was selected as the primary model for real-time weed detection due to its high-speed inference and accuracy. YOLOv8’s single-stage architecture predicts bounding boxes and class probabilities in a single pass, making it ideal for processing live drone feeds. We fine-tuned YOLOv8 on dataset to detect water hyacinth, using its Darknet backbone for robust feature extraction. The model was configured with three detection scales to identify weeds of varying sizes, from small clusters (0.5 m^2) to large mats (10 m^2). The class labels were defined as `weed` (for water hyacinth) and `background` (for water and native vegetation). YOLOv8’s multi-scale feature fusion enabled it to detect weeds at different distances and under varying lighting conditions, with a latency of 50 ms per image

3.4.2 RNN for Temporal Analysis

To model the seasonal growth patterns of water hyacinth, we developed an RNN with a Long Short-Term Memory (LSTM) architecture. The RNN used environmental data (e.g., temperature, pH, dissolved oxygen, nutrient levels) as input, with a sequence length of 10-time steps, to predict future weed density. The model was designed to capture long-term dependencies in the data, such as the correlation between temperature spikes and weed proliferation. The output was a predicted weed density score (0–1), which was used to schedule monitoring and harvesting operations proactively. The RNN achieved a mean squared error (MSE) of 0.09 and an R-squared value of 0.87 on the test set, indicating strong predictive capability.

3.5 Model Training and Evaluation

Training was conducted on Google Collab, utilizing its Tesla T4 GPU to accelerate computation. The dataset was split into training (70%), validation (20%), and test (10%) sets. YOLOv8 was trained for 150 epochs with a batch size of 16, using the Adam optimizer and a learning rate of 0.001. We applied transfer learning by initializing YOLOv8 with pre-trained weights from the COCO dataset, which improved convergence speed and reduced training time by 30%. U-Net was trained for 80 epochs with a binary cross-entropy loss function, using a batch size of 8. The RNN was trained for 60 epochs with a mean squared error loss function, using a batch size of 32.

Evaluation metrics were carefully selected to assess each model’s performance. For YOLOv8, It measure accuracy, precision, recall, and F1-score, achieving 94% accuracy, 0.92 precision, 0.91 recall, and 0.92 F1-score on the validation set. U-Net’s performance was evaluated using the Dice coefficient and Intersection over Union (IoU), recording a Dice coefficient of 0.89 and IoU of 0.80. The RNN’s predictive accuracy was assessed using MSE and R-squared, with an MSE of 0.09 and R-squared of 0.87, indicating strong predictive capability. To ensure robustness, It perform cross-validation with five folds, confirming that the models maintained consistent performance across different data subsets

3.6 System Deployment and Integration

The trained models were deployed on a local server for real-time operation, integrated with a web application built using Python Flask. Flask's lightweight framework was ideal for managing data flow and providing a user interface for monitoring. The application was hosted on a local server running on port 8082, with Flask handling API requests to transmit data between the drones, harvesters, and a central dashboard. The dashboard, rendered using Jinja2 templates, displayed real-time metrics, including weed detection results, environmental readings, and harvester status, enabling operators to make informed decisions.

The drones communicated with the Flask application via a local Wi-Fi network, transmitting image and sensor data at 5-second intervals. YOLOv8 processed the images on the server, generating bounding boxes and confidence scores for detected weeds. UNet's segmentation masks were overlaid on the images to identify target areas, and the coordinates were sent to the harvester. The harvester, equipped with an APM Pixhawk flight controller, executed precise weed removal using a cutting mechanism, guided by the drone data. Mission Planner software was used to plan flight paths and enable autopilot functionality, ensuring efficient navigation over the water body. The system's latency, from detection to action, was under 1.8 seconds, ensuring real-time operation.

IV. System Architecture

The system integrates hardware and software components to achieve seamless operation in aquatic environments. Below, we describe the architecture in detail

4.1 Hardware Components Used

1) Brushless DC (BLDC) motors - Provide efficient, high-speed rotation to power the drone's propellers for flight.

2) Electronic speed controllers (ESCs) - Regulate the speed and direction of the BLDC motors for precise drone movement.

3) APM Pixhawk flight controllers - Manage flight stability, navigation, and coordination of sensors and motors on both drones and harvesters.

4) 2.4 GHz receivers - Enable wireless communication between the drone and the ground control system for real-time command transmission.

5) High-resolution cameras (12 MP) - Capture detailed images or videos for monitoring and mapping the environment.

6) Ultrasonic sensors - Detect obstacles by emitting sound waves and measuring their return time to ensure safe navigation.

7) GPS/GNSS modules - Provide precise location data for navigation and waypoint tracking during operation.

8) Electric motors - Power the movement of the automated harvesters across the water surface with minimal environmental impact.

9) Adjustable blades - Cut aquatic weeds up to 10 cm below the water surface, allowing for effective weed removal.

10)Collection system - Gathers and stores the cut weeds on the harvester for later disposal on land. 4.2 Software Used

1) Python Flask - Acts as the web application framework, managing data routing, processing, and visualization, while enabling communication between drones and harvesters through a RESTful API and displaying real-time data via a dynamic dashboard using Jinja2 templating.

2) YOLOv8 (Ultralytics) - Performs high-speed object detection with multi-scale feature fusion, identifying weeds of varying sizes in drone images with a latency of 50 ms per image, and streams processed frames through the /webapp route using the video_detection function.

3) Google Colab - Provides a cloud-based environment with GPU access for model training, reducing training time by 60% compared to local hardware, and supports team collaboration for simultaneous model development and evaluation.

4) Mission Planner - Facilitates flight path planning, autopilot functionality, and system integration for drones, ensuring complete coverage of the water body through predefined routes, and delivers real-time telemetry data for monitoring.

V. Experimental Setup

The system was tested in a 10-hectare water body in Tamil Nadu, India, selected for its ecological and economic significance. The water body supported a local fishing community and provided irrigation for rice fields, but a severe water hyacinth infestation had reduced fish yields by 40% and irrigation efficiency by 30%.

5.1 Pre-Intervention Assessment

Before deployment, we conducted a baseline assessment of the water body. Dissolved oxygen levels averaged 4.1 mg/L, below the 6 mg/L threshold for healthy aquatic life. Sunlight penetration, measured with a Secchi disk, was limited to 18 cm due to dense weed mats. Water flow in irrigation channels was reduced by 50%, as confirmed by flow meter readings. Local stakeholders reported significant economic losses, with fishermen earning 50% less than five years prior and farmers struggling to irrigate their fields.

5.2 Data Collection and Preparation

Drones were deployed over a two-week period, capturing 6,500 images and 2,500 environmental readings. The images were annotated manually, with bounding boxes drawn around water hyacinth clusters, creating a labelled dataset for training. Environmental data was used to correlate weed growth with factors like temperature and nutrient levels, providing insights for the RNN model.

5.3 Field Testing

The system was tested in three phases:

1) Monitoring Phase: Drones mapped the water body in three days, achieving 96% coverage. They identified weed

clusters across 8.5 hectares, with YOLOv8 detecting weeds with 94% accuracy.

2) Detecting Phase: U-Net generated detect masks, distinguishing water hyacinth from native vegetation with a Dice coefficient of 0.89. It ensured that the harvester targeted only invasive weeds.

3) Harvesting Phase: The harvester removed 87% of the targeted weeds over five days, covering 8.5 hectares. The process was completed with two operators, compared to a team of 12 for manual removal.

VI. Results

The system demonstrated significant improvements in weed management, water quality, and operational efficiency.

6.1 Weed Detection and Removal

YOLOv8 achieved a detection accuracy of 94%, identifying water hyacinth clusters with high precision. The `video_detection` function processed drone imagery in real time, generating frames with bounding boxes and confidence scores, which were streamed via the Flask application. The harvester removed 87% of the targeted weeds, a substantial improvement over manual removal (50% efficiency) and mechanical harvesters (70% efficiency with collateral damage). U-Net's segmentation ensured that native vegetation was preserved, with less than 3% of non-target plants.

6.2 Environmental Impact

Post-intervention, water quality metrics improved significantly:

a. Dissolved oxygen levels increased by 32%, from 4.1 mg/L to 5.4 mg/L, approaching the healthy threshold for aquatic life.

b. Sunlight penetration improved by 155%, from 18 cm to 46 cm, promoting photosynthesis in underwater plants.

c. Water flow in irrigation channels increased by 42%, benefiting local farmers.

6.3 Biodiversity Recovery

Fish populations showed signs of recovery, with fishermen reporting a 22% increase in catch within one month. Native aquatic plants, previously suppressed by water hyacinth, began to regrow, as confirmed by visual inspections. The system's minimal impact on non-target species ensured that the ecosystem remained balanced.

6.4 Operational Efficiency

The system reduced manual labor by 72%, requiring only two operators compared to a team of 12 for manual removal. The total cost of operation was $480 per hectare, significantly lower than the $1,300 per hectare for manual methods. The use of Google Colab for training eliminated the need for expensive local hardware, further reducing costs. The Flask application's real-time dashboard, accessible via the `/chart` route, provided operators with actionable insights, improving decision-making efficiency.

6.5 Challenges and Limitations

Several challenges were encountered during implementation:

High Initial Cost: The cost of drones, sensors, and harvesters ($9,800) may be prohibitive for small communities.

Model Retraining: YOLOv8 required periodic retraining to adapt to new weed species and environmental conditions, such as seasonal changes in lighting and water clarity.

Scalability: The system's performance in larger water bodies, such as lakes or rivers, remains untested.

Battery Life: The drones' 30-minute flight time limited their coverage in a single session, requiring multiple flights to cover the entire water body.

6.6 Comparison with Existing Methods

Compared to manual removal, the system was significantly more efficient, reducing labor requirements by 72% and operational costs by 63%. Mechanical harvesters, while faster than manual methods, caused ecological disruption, with up to 20% of native plants affected, whereas the system minimized collateral damage to 3%. Chemical treatments, though effective, posed environmental risks, which approach avoided entirely by using a mechanical, AI-driven solution.

VII. Future Work

Future research will focus on addressing the identified challenges:

a) Cost Reduction: Exploring low-cost drone alternatives and open-source hardware to reduce the initial investment. For example, using off-the-shelf drones with a cost of $500 per unit could lower the overall system cost by 40%.

b) Scalability: Testing the system in larger water bodies, such as a 100-hectare lake, with multiple drones and harvesters operating in parallel. We plan to implement swarm intelligence algorithms to coordinate multiple drones, improving coverage and efficiency.

c) Predictive Analytics: Enhancing the RNN model with real-time environmental data to predict weed growth proactively, enabling preventive measures such as adjusting water flow or introducing natural predators.

d) Energy Efficiency: Developing solar-powered drones and harvesters to extend operational time and reduce environmental impact. Initial prototypes have shown a 50% increase in flight time using solar panels, and we aim to refine this design for field deployment.

e) Model Optimization: Optimizing YOLOv8 for edge deployment on the drones, reducing latency by processing images locally instead of on the server. It would require quantizing the model to run on resource-constrained hardware, such as a Raspberry Pi.

VIII. Conclusion

The study presents an AI-powered drone and harvester system for aquatic ecosystem restoration, leveraging YOLOv8, Python Flask, and Google Colab. The system integrates drone-based monitoring, real-time weed detection, and automated harvesting into a cohesive framework, offering a sustainable and efficient solution to aquatic weed infestations. Field tests demonstrated a 32% increase in dissolved oxygen levels, 87% weed removal efficiency, and a 72% reduction in manual labor, highlighting its potential to restore ecosystems and support local communities. Future work will focus on reducing costs, enhancing scalability, and incorporating predictive analytics to prevent infestations proactively, paving the way for broader adoption in environmental conservation efforts.

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