EPRA International Journal of Agriculture and Rural Economic Research (ARER)- Peer-Reviewed Journal
Volume: 14 | Issue: 4 | April 2026 | Journal DOI: 10.36713/epra0813| Impact Factor SJIF(2026): 8.801| ISSN: 2321 – 7847

REVOLUTIONIZING AQUATIC CROP MANAGEMENT WITH AI-BASED COMPUTER VISION: PRECISION WEED CONTROL FOR MAKHANA AND SINGHARA IN THE INDO-GANGETIC PLAINS

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ABSTRACT--

Aquatic crops such as fox nuts (Euryale ferox) and water chestnuts (Trapa natans) play a vital role in the agroeconomy of the Indo-Gangetic plains, particularly in Bihar, India, which dominates global Makhana production. However, productivity in these wetland-based systems is severely constrained by uncontrolled aquatic weed infestation, leading to significant yield losses and high dependence on labour-intensive manual removal practices. This review synthesizes current challenges and emerging technological interventions, focusing on the integration of artificial intelligence (AI) and computer vision for real-time weed detection, identification, and precision management.

The proposed AI-powered computer vision framework leverages drone-based multispectral imaging, underwater sensing, and deep learning algorithms such as YOLOv8, U-Net, and EfficientNet for accurate weed detection, segmentation, and classification. Coupled with GIS mapping, IoT integration, and robotic or precision herbicide delivery systems, this approach offers a scalable and sustainable alternative to conventional weed control methods. The review further highlights dataset development strategies, model pipelines, and field deployment mechanisms tailored for aquatic environments.

Adoption of such intelligent systems is expected to enhance crop yields by 15–25%, reduce labor dependency by up to 60%, and minimize herbicide usage, thereby contributing to economic efficiency and environmental sustainability. This paper underscores the transformative potential of AI-driven precision agriculture in modernizing aquatic crop production systems and addressing critical challenges in wetland farming ecosystems.

KEYWORDS: *Artificial Intelligence; Computer Vision; Precision Agriculture; Aquatic Weed Management; Makhana (Euryale ferox); Water Chestnut (Trapa natans); Deep Learning; Drone Imaging; Sustainable Agriculture; Indo-Gangetic Plains*--

INTRODUCTION

Aquatic cropping systems represent a unique and ecologically significant component of agriculture, particularly in the floodplain and wetland ecosystems of South Asia. Among these, fox nuts (*Euryale ferox* Salisb.), commonly known as Makhana, and water chestnuts (*Trapa natans* L.), known as Singhara, are economically important crops cultivated extensively in the Indo-Gangetic plains, especially in the state of Bihar, India. India contributes more than 90% of global Makhana production, with the crop holding Geographical Indication (GI) status as "Mithila Makhana," highlighting its regional and commercial importance (Kumar et al. 2019; Singh et al. 2021). These crops are valued not only for their nutritional richness—being high in protein, antioxidants, and micronutrients—but also for their role in supporting rural livelihoods and wetland-based agro-economies (Jha and Prasad 2018).

Despite their importance, productivity of these aquatic crops remains suboptimal due to several agronomic constraints, among which aquatic weed infestation is one of the most critical. Invasive and fast-growing weed species such as *Hydrilla verticillata*, *Eichhornia crassipes* (water hyacinth), *Lemna* spp. (duckweed), and *Ceratophyllum demersum* compete aggressively for nutrients, light, and dissolved oxygen, thereby significantly reducing crop growth and yield (Gopal 2013; Villamagna and Murphy 2010). Studies have reported yield reductions ranging from 25% to 40% in Makhana and up to 35% in water chestnut due to uncontrolled weed proliferation (ICAR-RCM 2020). The problem is exacerbated in deep-water systems where manual weed removal is physically demanding, time-consuming, and increasingly unsustainable due to labor shortages and rising wage costs.

Traditional weed management practices in aquatic systems rely almost exclusively on manual removal, which involves farmers working in waterlogged conditions for prolonged periods. This method is not only labor-intensive and inefficient but also poses serious occupational health risks (FAO 2017). Chemical control options are limited due to concerns over water contamination, non-target effects, and ecological imbalance in sensitive wetland ecosystems (Datta et al. 2019). Consequently, there is a pressing need for innovative, efficient, and environmentally sustainable weed management strategies tailored to aquatic cropping systems.

Recent advances in precision agriculture, particularly the integration of artificial intelligence (AI) and computer vision, offer promising solutions to address these challenges (Ahmad et al. 2023; Huang et al. 2023; Yang et al. 2023). AI-driven systems utilizing deep learning algorithms have demonstrated high accuracy in weed detection, classification, and mapping in terrestrial cropping systems (Kamilaris and Prenafeta-Boldú 2018; Hasan et al. 2021; Bakhshipour et al., 2022). Techniques such as convolutional neural networks (CNNs), object detection models like YOLO (You Only Look Once), and semantic segmentation architectures such as U-Net have been successfully applied for real-time plant identification and weed discrimination (Redmon et al. 2016; Ronneberger et al. 2015; Liakos et al., 2022). Furthermore, the integration of unmanned aerial vehicles (UAVs), multispectral imaging, and Internet of Things (IoT) technologies enables large-scale, high-resolution monitoring of crop fields with minimal human intervention (Zhang and Kovacs 2012; Milioto et al., 2023; Partel et al., 2023).

However, the application of these advanced technologies in aquatic environments remains relatively unexplored. The unique challenges of aquatic systems—such as water reflectance, submerged vegetation, and complex plant morphology—necessitate the development of specialized datasets and adaptive AI models. Emerging research suggests that combining aerial and underwater imaging with machine learning can significantly improve detection accuracy for aquatic weeds and enable targeted intervention strategies (Villa et al. 2017; Hunter et al. 2010).

In this context, the integration of AI-powered computer vision systems for aquatic weed detection, identification, and precision removal represents a transformative approach for enhancing productivity and sustainability in Makhana and Singhara cultivation. By reducing labor dependency, optimizing resource use, and enabling real-time decision-making, such systems have the potential to modernize traditional wetland agriculture and contribute to the broader goals of smart and sustainable farming.

This review uniquely focuses on the application of artificial intelligence–driven weed detection and management in aquatic cropping systems, particularly Makhana (*Euryale ferox*) and water chestnut (*Trapa natans*), which remain underexplored in current literature. It further integrates emerging approaches such as computer vision, UAV-based monitoring, and bioherbicide-based interventions to provide a comprehensive perspective on sustainable weed management in wetland agriculture (Villa et al. 2022; Zhang et al. 2024; Raza et al., 2022; Sathya et al., 2024).

2. IMPORTANCE OF AQUATIC CROPS IN THE INDO-GANGETIC PLAINS

Aquatic crops such as *Euryale ferox* (Makhana) and *Trapa natans* (water chestnut) are integral to the socio-economic fabric of eastern India. These crops thrive in stagnant water bodies, including ponds, oxbow lakes, and wetlands, making them uniquely adapted to flood-prone ecosystems. Makhana, in particular, has emerged as a high-value crop due to its nutritional properties and export potential (Singh et al. 2021; Sharma et al., 2022).

The Indo-Gangetic plains provide ideal agro-climatic conditions, including fertile alluvial soils, abundant water resources, and suitable temperature regimes for aquatic crop cultivation (Jha and Prasad 2018). However, despite favorable conditions, yield gaps persist due to suboptimal agronomic practices, especially inefficient weed management. Enhancing productivity in these systems is crucial for improving farmer incomes and ensuring sustainable utilization of wetland ecosystems (Table 1).

Table 1. Comparison of Makhana and Water Chestnut Production Systems

Parameter	Makhana (Euryale ferox)	Water Chestnut (Trapa natans)
Cultivation System	Pond & Field	Deep-water ponds
Water Depth	1–6 feet	3–5 feet
Average Yield	1.8–3.0 t/ha	3.5–5.0 t/ha
Major Regions	Bihar	Bihar, UP, WB, Assam
Weed Infestation Level	High	Very High
Labour Requirement	Very High	Very High
Cropping Intensity	2–3 crops/year	1–2 crops/year

3. AQUATIC WEED ECOLOGY AND ITS IMPACT ON CROP PRODUCTIVITY

3.1 Major Aquatic Weeds

Aquatic weed infestation is one of the most critical constraints limiting the productivity of Makhana (*Euryale ferox*) and Singhara (*Trapa natans*) cultivation systems. These weeds thrive in nutrient-rich, stagnant water bodies and exhibit aggressive growth patterns, enabling them to outcompete cultivated crops. Based on their growth habit and ecological niche, aquatic weeds are broadly classified into submerged, floating, and emergent types, each exerting distinct ecological pressures on crop systems.

Submerged weeds, such as *Hydrilla verticillata* and *Ceratophyllum demersum*, grow entirely beneath the water surface and form dense underwater canopies. These species are particularly problematic due to their rapid vegetative propagation through fragments, turions, and stolons. *Hydrilla verticillata*, often regarded as one of the most invasive aquatic plants globally, can colonize entire pond bottoms, forming thick mats that interfere with water circulation and nutrient dynamics.

Floating weeds, including *Eichhornia crassipes* (water hyacinth) and *Lemna* spp. (duckweed), occupy the water surface and reproduce at an extraordinary rate. *Eichhornia crassipes* is notorious for forming dense mats that can double in biomass within 7–15 days under favorable conditions, while *Lemna* spp. create continuous surface layers that restrict gas exchange. These weeds significantly alter the physicochemical properties of water bodies, often leading to hypoxic conditions (Table 2).

Emergent and floating-leaved weeds, such as *Nymphaea* spp., further complicate weed management due to their morphological similarity to crop plants like Makhana. This resemblance increases the likelihood of misidentification during manual weeding, resulting in accidental crop damage.

The ecological success of these aquatic weeds can be attributed to their high reproductive efficiency, phenotypic plasticity, and tolerance to a wide range of environmental conditions, including variable water depths, nutrient levels, and temperature regimes. Their ability to exploit eutrophic conditions commonly found in agricultural wetlands makes them dominant competitors in these ecosystems (Gopal 2013).

Table 2. Major Aquatic Weeds and Their Impact

Weed Species	Type	Key Impact on Crops
Hydrilla verticillata	Submerged	Nutrient competition, oxygen depletion
Eichhornia crassipes	Floating	Blocks sunlight (>95%), suppresses growth
Lemna spp. (Duckweed)	Floating	Surface coverage, inhibits seedling growth
Ceratophyllum demersum	Submerged	Entangles crop stems
Nymphaea spp.	Floating	Misidentification with crop plants

3.2 Mechanisms of Crop Loss

Aquatic weeds adversely affect crop productivity through a combination of physiological, ecological, and mechanical interactions, leading to substantial yield reductions and increased production costs.

One of the primary mechanisms is light interception, particularly by floating weeds such as *Eichhornia crassipes* and *Lemna* spp. These species form dense surface mats that can block up to 90–95% of incident sunlight, drastically reducing photosynthetically active radiation (PAR) reaching submerged crop leaves. This limitation in light availability directly suppresses photosynthesis, thereby inhibiting plant growth and biomass accumulation.
Another critical factor is nutrient competition. Submerged weeds like *Hydrilla verticillata* actively absorb dissolved nutrients, particularly nitrogen and phosphorus, from the water column. In nutrient-limited systems, this competition deprives crop plants of essential resources required for growth and reproductive development, ultimately reducing yield potential.

Oxygen depletion is an additional consequence of dense weed proliferation. Thick weed mats impede atmospheric oxygen diffusion into the water and increase biological oxygen demand (BOD) through decomposition processes. Reduced dissolved oxygen levels negatively affect root respiration and microbial activity, disrupting nutrient cycling and leading to suboptimal plant health.

Aquatic weeds also cause physical obstruction within the cropping system. Species such as *Ceratophyllum demersum* create tangled masses that interfere with plant spacing, restrict water movement, and complicate harvesting operations. In extreme cases, dense weed growth can completely choke water bodies, rendering them unsuitable for cultivation.

Furthermore, aquatic weeds contribute to microenvironmental changes, including increased water temperature, altered pH, and accumulation of organic matter, which can favor pest and disease incidence. These indirect effects further exacerbate crop stress and yield losses.

Collectively, these mechanisms result in significant reductions in crop productivity, often ranging from 25% to 40% depending on weed density and management practices(Fig 1). Additionally, the increased labor and input costs associated with weed control place a substantial economic burden on farmers, particularly in traditional manual systems (Villamagna and Murphy 2010).

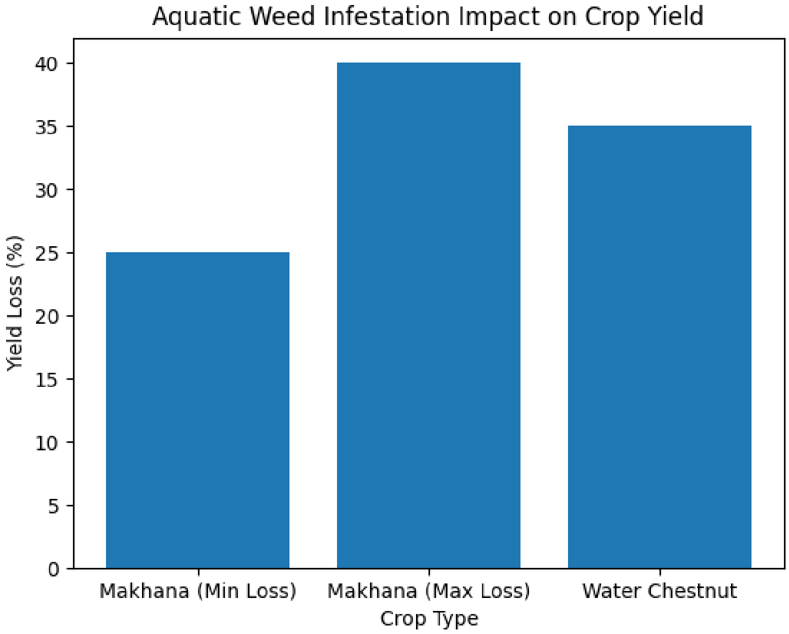

Figure 1. Aquatic Weed Infestation Impact on Crop Yield

A bar graph showing yield reduction:

- Makhana: 25–40% loss
- Water Chestnut: up to 35% loss

4. LIMITATIONS OF CONVENTIONAL WEED MANAGEMENT

Weed management in aquatic cropping systems such as Makhana (*Euryale ferox*) and Singhara (*Trapa natans*) remains largely dependent on traditional, labor-intensive practices, with minimal technological intervention. Although manual removal has been the predominant method for decades, its effectiveness is increasingly constrained by economic, environmental, and social factors.

The most widely practiced approach is manual weeding, wherein farmers physically enter water bodies—often chest-deep—and remove weeds by hand. While this method allows selective removal and avoids chemical contamination, it suffers from several critical limitations.

One of the primary constraints is the high labor requirement, often reaching 45–60 man-days per hectare per season. This not only increases the cost of cultivation but also creates dependency on seasonal labor availability, which is becoming increasingly scarce due to rural-to-urban migration and diversification of livelihoods.

In addition, manual weeding poses significant occupational health risks. Farmers are exposed to prolonged water immersion, leading to skin infections, parasitic diseases, and musculoskeletal disorders. The physically demanding nature of the work, often performed under harsh environmental conditions, further reduces labor efficiency and limits scalability.

Another major drawback is low operational efficiency. Manual removal is often incomplete, particularly for submerged weeds such as *Hydrilla verticillata* and *Ceratophyllum demersum*, which can regenerate rapidly from small fragments. As a result, repeated weeding cycles are required within a single cropping season, increasing both labor costs and time investment. Moreover, the difficulty in distinguishing crop plants from morphologically similar weeds (e.g., *Nymphaea* spp.) can lead to inadvertent crop damage.

The use of mechanical weed control methods in aquatic environments remains limited due to practical challenges. Conventional mechanical weeders are not well-suited for deep-water or uneven pond conditions, and their deployment is constrained by accessibility, cost, and maintenance requirements. Floating mechanical harvesters exist but are often economically unviable for smallholder farmers and lack precision in selective weed removal.

Similarly, chemical weed management options are restricted in aquatic systems due to serious environmental and ecological concerns. The application of herbicides in water bodies poses risks of contamination, affecting non-target aquatic flora and fauna, as well as downstream ecosystems. Residual toxicity can disrupt biodiversity, alter water quality, and pose potential risks to human health, particularly in systems where water is used for multiple purposes. Consequently, herbicide use is either minimal or discouraged in many wetland-based cropping systems (Datta et al. 2019).

Furthermore, conventional methods lack real-time monitoring and decision-support capabilities, resulting in reactive rather than proactive weed management. Farmers typically rely on visual assessment, which is subjective and often delayed, allowing weeds to establish and spread before intervention.

Taken together, these limitations highlight the inefficiency, unsustainability, and economic burden of traditional weed management approaches in aquatic agriculture. The inability of manual, mechanical, and chemical methods to provide timely, precise, and scalable solutions underscores the urgent need for innovative, technology-driven alternatives, such as AI-based precision weed management systems.

5. ARTIFICIAL INTELLIGENCE AND COMPUTER VISION IN AGRICULTURE

5.1 Overview of AI in Precision Agriculture

Artificial intelligence (AI) has emerged as a transformative force in modern agriculture, enabling the transition from conventional practices to data-driven, site-specific crop management systems. By leveraging large volumes of agronomic, environmental, and imaging data, AI facilitates precise decision-making that enhances productivity, resource-use efficiency, and sustainability.

Machine learning (ML) and deep learning (DL), the core components of AI, allow automated extraction of complex patterns from heterogeneous datasets such as satellite imagery, sensor data, and field observations. These technologies support a wide range of agricultural applications, including crop health monitoring, yield prediction, disease diagnosis, and weed management. Unlike traditional statistical methods, deep learning models—particularly convolutional neural networks (CNNs)—can learn hierarchical feature representations directly from raw data, significantly improving prediction accuracy and robustness (Kamilaris and Prenafeta-Boldú 2018).

In precision agriculture, AI-driven systems are often integrated with Internet of Things (IoT) devices, remote sensing platforms, and Geographic Information Systems (GIS) to enable real-time monitoring and adaptive management. This integration is particularly valuable in complex environments such as aquatic cropping systems, where spatial and temporal variability is high. AI thus plays a crucial role in optimizing inputs, reducing operational costs, and minimizing environmental impacts.

5.2 Computer Vision Techniques

Computer vision, a specialized domain within AI, focuses on enabling machines to interpret and analyze visual information from images and videos. In agricultural applications, computer vision has gained prominence for its ability to perform automated, non-destructive, and high-throughput analysis of crops and weeds.
Several key computer vision techniques are widely employed in weed detection and management:

- **Object Detection**
  Object detection models, such as the YOLO (You Only Look Once) family, are designed to identify and localize objects within an image by generating bounding boxes and class labels. These models are highly efficient and capable of real-time performance, making them suitable for field deployment using drones or edge devices. In weed management, object detection enables rapid identification of weed presence and spatial distribution across large areas.
- **Image Segmentation:**
  Semantic segmentation techniques, particularly architectures like U-Net, provide pixel-level classification of images, allowing precise delineation between crops, weeds, and background elements. This level of detail is critical in scenarios where weeds are closely intermixed with crops or exhibit similar morphological characteristics. Segmentation outputs can be directly used for generating weed density maps and guiding precision interventions.
- **Image Classification:**

Classification models based on deep CNN architectures (e.g., ResNet, EfficientNet) are used to categorize images or image regions into predefined classes, such as specific weed species. Accurate species identification is essential for implementing targeted management strategies, including species-specific bioherbicide application or mechanical removal.

These computer vision approaches have demonstrated high accuracy and robustness in terrestrial cropping systems, often achieving detection accuracies exceeding 90% under controlled conditions (Hasan et al. 2021). However, their application in aquatic environments presents additional challenges, including water reflectance, variable lighting conditions, and the presence of submerged vegetation. Addressing these complexities requires adaptation of existing models and the development of specialized datasets tailored to aquatic ecosystems.

Overall, the integration of computer vision with AI-based decision systems provides a powerful framework for automated weed detection, classification, and precision management, paving the way for next-generation smart agriculture solutions.

6. AI-BASED WEED DETECTION TECHNOLOGIES (FIG 2).

6.1 Deep Learning Models

Recent advances in deep learning have significantly enhanced the accuracy and efficiency of weed detection systems, particularly under complex and heterogeneous field conditions. These models are capable of learning intricate spatial and spectral features from large image datasets, enabling robust discrimination between crops and weeds even under challenging scenarios such as occlusion, variable lighting, and mixed vegetation.

- **YOLO (You Only Look Once):**
  YOLO-based architectures represent state-of-the-art real-time object detection frameworks that process entire images in a single forward pass. Their high inference speed and accuracy make them particularly suitable for deployment on drones and edge devices for real-time weed detection. YOLO models can simultaneously detect multiple weed instances and provide spatial coordinates, facilitating rapid field-level assessment (Redmon et al. 2016).

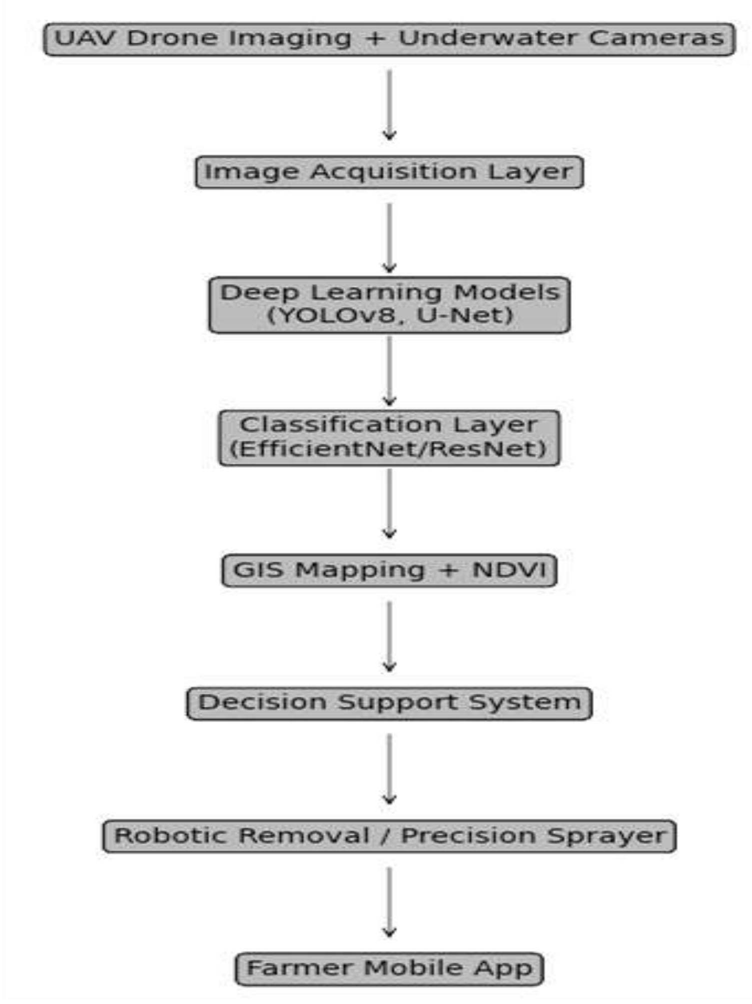

Figure 2. AI-Based Aquatic Weed Detection System Architecture

- **U-Net (Semantic Segmentation):**
  U-Net is a convolutional neural network architecture designed for precise pixel-level segmentation, enabling accurate delineation of weed boundaries from crop canopies and water backgrounds. Its encoder–decoder structure with skip connections allows the model to retain both contextual and fine-grained spatial information, making it highly effective in complex agricultural environments, including aquatic systems where visual overlap is common (Ronneberger et al. 2015).
- **EfficientNet and ResNet (Image Classification):**
  These advanced convolutional neural network architectures are widely used for weed species classification. ResNet employs residual learning to overcome vanishing gradient issues in deep networks, while EfficientNet optimizes model scaling for improved accuracy and computational efficiency. These models are particularly useful for identifying specific weed species, enabling targeted management strategies such as species-specific bioherbicide application.

Collectively, these deep learning models enable high-precision detection, segmentation, and classification, forming the core of AI-based weed management systems. Their integration allows end-to-end automation—from weed identification to actionable decision-making—under real-world field conditions (Table 3 and Flowchart 1).

6.2 Remote Sensing and UAV Integration

The integration of AI with remote sensing technologies, particularly Unmanned Aerial Vehicles (UAVs), has revolutionized large-scale agricultural monitoring. UAVs equipped with high-resolution RGB and multispectral sensors provide detailed spatial and temporal data, enabling continuous surveillance of crop fields.

Multispectral imaging facilitates the calculation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which is widely used to assess plant health and distinguish between crops and weeds based on their spectral signatures. Weeds often exhibit distinct reflectance characteristics compared to cultivated plants, allowing their identification and mapping across large areas (Zhang and Kovacs 2012).

In aquatic systems, UAV-based monitoring is particularly advantageous as it allows non-invasive, rapid assessment of inaccessible or waterlogged areas. When combined with AI models, UAV imagery can be processed to generate weed density maps, hotspot identification, and temporal growth patterns, enabling proactive and site-specific weed management.

6.3 IoT and Edge Computing

The integration of Internet of Things (IoT) technologies and edge computing plays a crucial role in enabling real-time, autonomous weed detection and management systems. IoT devices, including environmental sensors and imaging units, continuously collect data on parameters such as water quality, temperature, and nutrient levels, which influence weed growth dynamics.

Edge computing devices, such as NVIDIA Jetson Nano or similar embedded systems, allow on-site processing of image data using trained AI models, eliminating the need for continuous cloud connectivity. This significantly reduces latency and bandwidth requirements while enabling real-time decision-making in the field.

Table 3. AI Models Used in Weed Detection

Model	Function	Advantages	Limitations
YOLOv8	Object Detection	Fast, real-time detection	Needs large dataset
U-Net	Segmentation	High precision boundary detection	Computationally intensive
ResNet-50	Feature Extraction	Deep feature learning	Overfitting risk
EfficientNet	Classification	High accuracy, efficient scaling	Requires tuning
LSTM	Prediction	Temporal analysis capability	Complex training

Flowchart 1. AI-Based Weed Detection Pipeline

Start
↓
Image Capture (Drone + Underwater Sensors)
↓
Pre-processing (Noise removal, normalization)
↓
Weed Detection (YOLOv8)
↓
Segmentation (U-Net)
↓
Species Classification (EfficientNet)
↓
Weed Density Mapping (GIS + NDVI)
↓
Decision Making
↓
Precision Action (Robot / Sprayer)
↓
End

Such systems can instantly process incoming data, detect weed infestations, and trigger appropriate actions—such as activating robotic weed removal units or guiding precision spraying mechanisms. Additionally, integration with mobile-based decision support systems ensures that farmers receive timely alerts and actionable insights.

Overall, the convergence of deep learning, UAV-based remote sensing, IoT, and edge computing creates a powerful technological ecosystem for precision weed management, offering scalable, efficient, and sustainable solutions for both terrestrial and aquatic agricultural systems.

7. CHALLENGES IN AQUATIC WEED DETECTION USING AI

Despite significant progress in artificial intelligence and computer vision, the application of these technologies to aquatic weed detection remains constrained by several environment-specific technical and operational challenges. Unlike terrestrial systems, aquatic environments present unique optical, biological, and data-related complexities that can adversely affect model performance and reliability.

One of the primary challenges is water surface reflectance and glare, which can significantly degrade image quality. Sunlight reflection, wave-induced distortions, and varying illumination conditions introduce noise and reduce contrast in captured images, making it difficult for vision models to accurately distinguish between water, crops, and weeds. These effects are particularly pronounced in UAV-based imaging, where viewing angles and time-of-day variations further influence spectral signatures.

Another major limitation is the complexity of detecting submerged vegetation. Submerged weeds such as *Hydrilla verticillata* and *Ceratophyllum demersum* are often partially or fully obscured by the water column, leading to reduced visibility and distorted appearance due to light attenuation and scattering. Conventional RGB imaging is often insufficient to capture these features reliably, necessitating the use of multispectral or underwater imaging systems combined with advanced image enhancement techniques.

The morphological similarity between crop plants and certain weed species further complicates detection tasks. For instance, floating-leaved weeds such as *Nymphaea* spp. can closely resemble Makhana leaves, increasing the likelihood of misclassification by AI models. This challenge is particularly critical in precision agriculture, where incorrect identification can lead to unintended crop removal or ineffective weed control measures.

A significant bottleneck in developing robust AI models is the limited availability of high-quality, annotated datasets specific to aquatic ecosystems. Most existing agricultural datasets are designed for terrestrial crops and lack representation of aquatic weeds under diverse environmental conditions. The scarcity of labeled data across different growth stages, water depths, and seasonal variations restricts the generalizability and scalability of trained models.

In addition to these factors, environmental variability—including fluctuations in water turbidity, nutrient levels, and climatic conditions—introduces further complexity, requiring models to be highly adaptive and resilient. The integration of multi-source data (e.g., aerial, underwater, and sensor-based inputs) also presents challenges in data fusion and synchronization.

Addressing these challenges necessitates the development of specialized, large-scale annotated datasets, along with the design of adaptive and hybrid AI models capable of handling noisy, heterogeneous data. Approaches such as multispectral imaging, domain adaptation, transfer learning, and sensor fusion are increasingly being explored to improve detection accuracy in aquatic environments (Villa et al. 2017).

Overall, overcoming these limitations is critical for the successful deployment of AI-based weed detection systems in aquatic agriculture and for realizing their full potential in precision weed management.

8. DATASET DEVELOPMENT AND MODEL TRAINING

The performance and reliability of AI-based weed detection systems are fundamentally dependent on the quality, diversity, and representativeness of training datasets. In aquatic cropping systems, dataset development is particularly critical due to the high variability in environmental conditions and the complex visual characteristics of water–plant interactions. Robust datasets enable deep learning models to generalize effectively across different field scenarios and improve detection accuracy under real-world conditions.

A key requirement is the collection of diverse and representative imagery encompassing variations in seasons, growth stages, water depths, lighting conditions, and levels of weed infestation. Aquatic ecosystems are highly dynamic, and weed appearance can change significantly over time due to phenological development and environmental fluctuations. Therefore, datasets must capture this variability to ensure model robustness and scalability.

The incorporation of multispectral imaging further enhances dataset quality by providing additional spectral information beyond the visible range. Data from Near-Infrared (NIR) and red-edge bands are particularly useful for distinguishing between crop plants, weeds, and water surfaces based on their differential reflectance properties. Such spectral features improve the accuracy of vegetation indices (e.g., NDVI) and strengthen the capability of models to detect subtle differences between target classes.

Another critical aspect is high-quality annotation and labeling. Accurate, pixel-level or object-level annotations—validated by domain experts such as agronomists or weed scientists—are essential for training supervised learning models. In aquatic systems, annotation is more challenging due to overlapping vegetation, water distortion, and morphological similarities between species, making expert validation indispensable for ensuring dataset reliability.

To further enhance model performance, data augmentation techniques are employed to artificially expand the dataset and improve generalization. Techniques such as rotation, scaling, flipping, brightness adjustment, noise injection, and synthetic image generation help simulate real-world variability and reduce the risk of overfitting. Augmentation is particularly important in aquatic datasets, where collecting large volumes of labeled data can be resource-intensive.

In addition, transfer learning approaches are commonly utilized to leverage pre-trained models developed on large-scale datasets. Publicly available datasets such as PlantVillage and DeepWeeds provide a valuable starting point for model development; however, they are primarily focused on terrestrial crops and weed species. Consequently, these datasets require domain adaptation and fine-tuning to account for the unique characteristics of aquatic environments, including water background, submerged vegetation, and spectral distortions (Hasan et al. 2021).

Model training typically involves iterative processes of training, validation, and testing, using metrics such as accuracy, precision, recall, F1-score, and mean average precision (mAP) to evaluate performance. Optimization techniques, including hyperparameter tuning and model regularization, are applied to improve predictive capability and computational efficiency.

Overall, the development of large-scale, well-annotated, and environment-specific datasets, combined with advanced training strategies, is essential for building reliable AI models tailored to aquatic weed detection. Such efforts will play a pivotal role in enabling accurate, scalable, and field-deployable precision weed management systems (Flowchart 2).

9. PRECISION WEED MANAGEMENT STRATEGIES

The integration of artificial intelligence with advanced engineering solutions has enabled the development of precision weed management strategies that are more efficient, targeted, and sustainable compared to conventional approaches. These strategies focus on site-specific intervention, minimizing resource use while maximizing weed control efficiency, particularly in complex aquatic cropping systems(Table 4).

Flowchart 2. Dataset Development Workflow

Field Survey
↓
Image Collection (RGB + Multispectral)
↓
Data Annotation (Expert labelling)
↓
Data Augmentation
↓
Model Training
↓
Validation & Testing
↓
Deployment

Table 4. Comparison of Weed Management Approaches

Method	Efficiency	Cost	Environmental Impact	Limitations
Manual Weeding	Medium	High	Low	Labour-intensive
Mechanical Removal	Medium	Medium	Moderate	Limited in deep water
Chemical Herbicides	High	Medium	High	Ecological risks
AI-Based Precision	Very High	Moderate	Low	Initial investment required

9.1 Robotic Weed Removal

Autonomous and semi-autonomous robotic weed removal systems represent a promising alternative to manual labor in aquatic environments. These systems are designed to operate on or within water bodies using floating platforms or amphibious mechanisms equipped with mechanical cutters, suction devices, or gripping tools.

AI-powered vision systems guide these robots to identify and selectively remove weed patches, ensuring minimal disturbance to crop plants. Such precision is particularly valuable in Makhana and Singhara cultivation, where crops and weeds often coexist in close proximity.

Robotic systems offer several advantages, including:

- Reduced labor dependency and operational costs
- Enhanced safety by minimizing human exposure to waterborne hazards
- Consistent and repeatable performance
- Scalability for large water bodies

However, challenges such as high initial costs, navigation in uneven aquatic terrains, and maintenance requirements need to be addressed for widespread adoption.

9.2 Precision Herbicide Application

Precision herbicide application involves the use of AI-guided spraying systems that deliver herbicides only to identified weed targets, rather than broadcasting chemicals across the entire field. This approach utilizes real-time weed detection data generated through computer vision models to guide micro-sprayers or smart nozzles.

Key advantages include:

- Significant reduction in herbicide usage, often by 30–70%
- Minimized environmental contamination, particularly important in aquatic ecosystems
- Improved efficacy through targeted application at optimal growth stages
- Lower input costs and reduced risk of herbicide resistance

In aquatic systems, precision spraying can be implemented using drone-mounted sprayers or floating robotic platforms. Additionally, this approach can be extended to the application of bioherbicides, further enhancing sustainability.

9.3 Decision Support Systems

AI-driven Decision Support Systems (DSS) play a critical role in translating complex data into actionable insights for farmers and stakeholders. These systems integrate outputs from AI models, remote sensing platforms, and IoT sensors to provide real-time recommendations for weed management.

Modern DSS platforms are typically delivered through mobile applications or web-based interfaces, designed to be user-friendly and accessible to farmers. Key functionalities include:

- Weed density and distribution maps generated from UAV or sensor data
- Early warning alerts for emerging weed infestations
- Species-specific management recommendations
- Scheduling of interventions (mechanical, chemical, or biological)
- Economic analysis and cost-benefit insights

In regions like the Indo-Gangetic plains, incorporating multilingual interfaces (e.g., Hindi and regional languages) enhances accessibility and adoption among smallholder farmers(Flowchart 3).

Flowchart 3. Precision Weed Management System

Weed Detection
↓
Hotspot Identification
↓
Action Selection
→ Mechanical Removal

→ Micro-Spraying
↓
Execution via Autonomous System
↓
Monitoring & Feedback

Overall, these precision weed management strategies—combining robotics, targeted application technologies, and intelligent decision support—form the foundation of next-generation integrated weed management systems. Their adoption has the potential to significantly improve productivity, reduce environmental impact, and promote sustainable intensification of aquatic agriculture.

10. SOCIO-ECONOMIC AND ENVIRONMENTAL IMPACT

The adoption of AI-powered weed management systems in aquatic cropping systems such as Makhana (*Euryale ferox*) and Singhara (*Trapa natans*) has far-reaching socio-economic and environmental implications. By replacing labor-intensive and inefficient conventional practices with intelligent, precision-based interventions, these technologies contribute to enhanced productivity, improved livelihoods, and sustainable ecosystem management.

One of the most significant benefits is increased crop productivity, with studies and pilot implementations indicating potential yield improvements of 15–25% under effective weed control. By enabling early detection and timely intervention, AI systems minimize crop–weed competition, ensuring optimal utilization of nutrients, light, and space.

Another major advantage is cost reduction, particularly in terms of labor and input use. Traditional manual weeding requires substantial labor investment, often accounting for a significant portion of total cultivation costs. AI-based systems reduce dependence on manual labor through automation and targeted interventions, leading to lower operational expenses. Additionally, precision application of herbicides or bioherbicides reduces input wastage, further enhancing cost efficiency.

From an environmental perspective, these technologies promote sustainable agricultural practices. Precision weed management significantly reduces the need for blanket herbicide application, thereby minimizing chemical runoff, water contamination, and adverse impacts on non-target aquatic organisms. This is especially critical in wetland ecosystems, which are highly sensitive and play an essential role in maintaining biodiversity and ecological balance.

Farmer health and safety are also improved through reduced physical exposure to hazardous working conditions. By minimizing the need for prolonged manual labor in waterlogged fields, AI-enabled systems help prevent occupational risks such as waterborne infections, skin diseases, and musculoskeletal strain.

In addition, the adoption of AI technologies supports digital transformation in agriculture, facilitating better data collection, monitoring, and decision-making. It empowers farmers with real-time information and enhances their capacity to respond proactively to field conditions. This aligns closely with national and global initiatives promoting smart farming, climate-resilient agriculture, and resource-use efficiency.

Moreover, these systems can contribute to rural employment diversification, creating opportunities in areas such as drone operation, data management, and agri-tech services. Over time, this can strengthen the agricultural value chain and support inclusive economic growth.

Overall, AI-powered weed management technologies represent a holistic solution that integrates productivity enhancement with environmental conservation and socio-economic development. Their adoption is consistent with the broader goals of sustainable agriculture and digital innovation outlined by global frameworks (FAO 2017).

11. FUTURE PROSPECTS AND RESEARCH DIRECTIONS

The application of artificial intelligence in aquatic weed management is still at a nascent stage, offering substantial scope for innovation and interdisciplinary research. To fully realize the potential of AI-driven precision agriculture in wetland ecosystems, future efforts must focus on technological advancement, system integration, and large-scale deployment strategies.

A key priority is the development of aquatic-specific AI models tailored to the unique challenges of water-based environments. Unlike terrestrial systems, aquatic ecosystems involve complex optical properties, submerged vegetation, and dynamic backgrounds. Therefore, customized deep learning architectures capable of handling water reflectance, turbidity, and mixed vegetation layers are essential for improving detection accuracy and robustness.

Another critical research direction is the integration of multi-sensor data, combining inputs from aerial (UAV-based multispectral imaging), underwater cameras, and ground-based IoT sensors. Such sensor fusion approaches can provide a more comprehensive understanding of weed distribution across both surface and subsurface layers. Advanced data fusion techniques and hybrid AI models will be required to effectively process and interpret these heterogeneous datasets.

The expansion of large-scale, annotated aquatic datasets is equally important. There is a pressing need to develop open-access, standardized datasets that capture diverse weed species, growth stages, and environmental conditions across different geographic regions. Collaborative initiatives involving research institutions and agricultural agencies can accelerate dataset development and improve model generalizability.

To ensure practical applicability, emphasis must also be placed on the development of low-cost, farmer-friendly technologies. Affordable UAV platforms, edge-computing devices, and mobile-based decision support systems should be designed with simplicity, reliability, and accessibility in mind. Localization features, including regional language interfaces and offline functionality, will further enhance adoption among smallholder farmers.

In addition, policy support and institutional frameworks will play a crucial role in promoting the adoption of AI technologies in wetland agriculture. Government initiatives can facilitate technology dissemination through subsidies, training programs, and infrastructure development. Establishing regulatory guidelines for the safe and effective use of AI, drones, and precision input systems will also be necessary.

Despite significant progress, several research gaps must be addressed to advance AI-based aquatic weed management systems. There is a pressing need for the development of comprehensive, annotated datasets tailored to aquatic environments, capturing diverse species, growth stages, and ecological conditions. Additionally, improving real-time deployment capabilities through robust edge computing and field-adaptable hardware remains a key challenge. Another important gap is the limited integration of AI-based detection systems with bioherbicide-based control strategies, which offers significant potential for developing sustainable, precision-driven weed management solutions. Addressing these gaps will be essential for translating technological advancements into practical, field-level applications.

Finally, multi-stakeholder collaboration will be essential for scaling these innovations. Partnerships among academic institutions, government agencies, private agri-tech companies, and farmer organizations can drive research, commercialization, and field-level implementation. Such collaborative ecosystems will help bridge the gap between laboratory research and real-world application.

In conclusion, advancing AI-based aquatic weed management requires a holistic and integrated approach, combining scientific innovation with socio-economic considerations. With sustained research, supportive policies, and collaborative efforts, these technologies have the potential to transform wetland agriculture into a more productive, sustainable, and technologically empowered sector.

Concept: Aquatic Field → Drone Imaging → AI Model → Weed Map → Precision Removal → Increased Yield

The link for concept -https://singhravi.github.io/emerging-tech-for-ponds-management/

12. CONCLUSION

Aquatic weed infestation continues to be a critical constraint limiting the productivity and profitability of Makhana (*Euryale ferox*) and water chestnut (*Trapa natans*) cultivation systems. Conventional weed management practices, primarily based on manual labor, are increasingly becoming economically unviable, labor-intensive, and operationally inefficient, particularly in the context of shrinking rural workforce availability and rising production costs.

The emergence of AI-powered precision agriculture technologies, including computer vision, UAV-based remote sensing, IoT integration, and automated intervention systems, offers a transformative pathway for addressing these challenges. By enabling real-time weed detection, accurate species identification, and site-specific management, these technologies facilitate timely and efficient control of aquatic weeds while minimizing resource use and environmental impact.

Furthermore, the integration of robotic weed removal systems, precision spraying technologies, and bioherbicide-based interventions enhances the sustainability and adaptability of weed management strategies in sensitive wetland ecosystems. Such approaches not only improve crop productivity—potentially increasing yields by 15–25%—but also reduce labor dependency, lower input costs, and mitigate ecological risks associated with indiscriminate chemical use.

However, the successful deployment of these technologies at scale will depend on continued advancements in aquatic-specific AI models, robust dataset development, cost-effective system design, and user-friendly decision support tools. Equally important is the role of policy support, capacity building, and multi-stakeholder collaboration in facilitating adoption among farmers, particularly in resource-constrained regions.

This review distinctly highlights the potential of AI-driven precision weed management specifically tailored for aquatic cropping systems, an area that has received limited attention compared to terrestrial agriculture. By integrating advanced technologies with eco-friendly approaches such as bioherbicides, it provides a holistic framework for sustainable intensification of wetland farming systems. In conclusion, AI-driven precision weed management represents a paradigm shift in aquatic agriculture, bridging the gap between traditional practices and modern technological solutions. With sustained research, innovation, and institutional support, these systems have the potential to significantly enhance productivity, ensure environmental sustainability, and contribute to the long-term resilience of wetland-based farming systems.

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