# IoT-Enabled Smart Aquaponics System with AI-Driven Monitoring for Optimized Crop and Fish Growth in Controlled Environments

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#### Introduction

#### **Background:**

Aquaponics combines aquaculture and hydroponics, creating a symbiotic environment where fish waste provides nutrients for plants while plants filter water for fish. Traditional aquaponics systems face challenges in maintaining optimal parameters for both fish and crop health, leading to suboptimal yields and resource inefficiency.

#### **Problem Statement:**

- ❖Conventional aquaponics relies on manual monitoring (labor-intensive)
- ❖Delayed detection of water quality anomalies causes mortality events
- ❖Suboptimal environmental conditions reduce productivity by 30-40%
- **❖**Lack of predictive analytics prevents proactive system management

Significance: This research addresses UN SDG 2 (Zero Hunger) and SDG 12 (Responsible Production) by developing sustainable, intelligent food production technology capable of increasing yields while reducing water consumption by 90% compared to conventional agriculture.

### **Materials and Methods**



# **Study Location:**

Centre for Protected **Cultivation Technology** (CPCT),ICAR-IARI, New Delhi

Fig. IoT – Driven Vertical Hydroponic Farming Greenhouse

#### **IoT-Enabled Smart Aquaponics System Architecture** Multi-Layer Al-Driven Monitoring & Control System



# Layer 2: Edge Computing (Processing Layer)

Layer 3: AI/ML Framework (Intelligence Layer)

- ESP32-DevKitC Microcontroller Unit
- Real-time data acquisition
- Local anomaly detection Edge Al processing
- 240 MHz dual-core processor

#### Communication Primary: WiFi (2.4 GHz)

- Backup: LoRaWAN
- Data transmission: Real-time Protocol: MQTT/HTTP
- Latency: <2 seconds</li>

#### Image Processing YOLOv8 Model Plant disease detection 8,500 training images CNN-LSTM Hybrid Fish behavior analysis Movement tracking

Time-Series Prediction LSTM Network 3 layers, 128 units each Optimizer: Adam Input Window 168 hours (1 week) Prediction: 24h ahead Loss Function: MSE Accuracy: 94.7%

Control System Deep Q-Network (DQN) Reinforcement Learning Autonomous optimization State Space 12 environmental params 8 actuator controls Reward: Growth + Stability Response: <2 sec

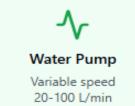
#### Layer 4: Automated Controls (Actuation Layer)

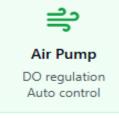


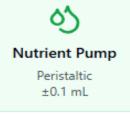
PWM control

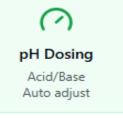
Batch: 32 | Epochs: 150

Learning rate: 0.001









15K+

Data Points/Hour

#### Layer 5: Cloud & Data Management (Application Layer)



- Real-time data logging
- 15,000+ points/hour

- Backup & redundancy
- · Historical analytics

# Data Analytics

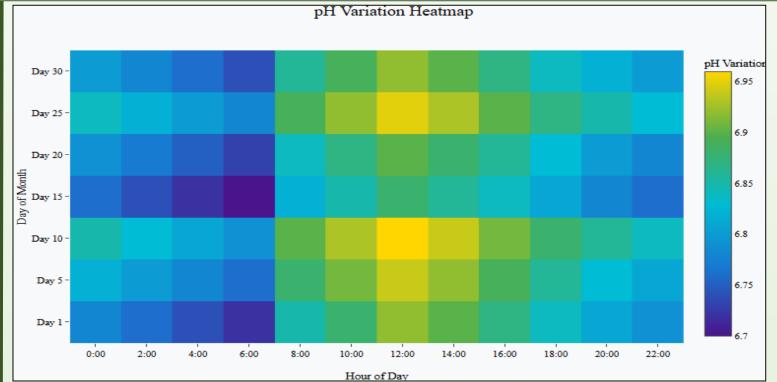
- Predictive modeling
- Trend analysis
- Performance metrics
- Alert generation

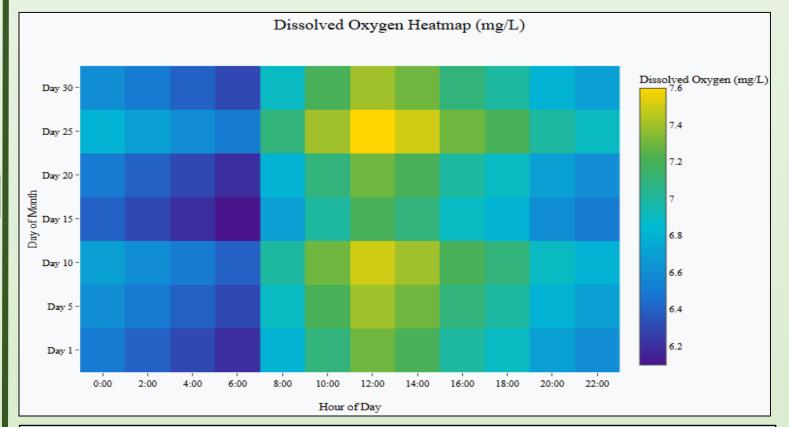
#### √ User Interface · Web dashboard

- Mobile app
- Real-time monitoring
- Remote control

72h

**Results** 





### Fig. pH and Do Variation Heatmap (30 Days x 24 Hours) **TABLE 1: Fish Growth Performance Metrics - Channa striata**

# (Snakehead Murrel)

Growth Parameter	Initial (Day 0)	Smart System (Mean ± SD)	Conventional (Mean ± SD)	Performance Improvement
Individual Weight (g)	$45.2 \pm 3.1$	$186.4 \pm 12.3$	145.6 ± 18.7	+28.0%
Total Length (cm)	$12.5 \pm 0.6$	24.8 ± 1.4	21.3 ± 2.1	+16.4%
Condition Factor (K)	$1.85 \pm 0.08$	$1.23 \pm 0.06$	$1.18 \pm 0.09$	+4.2%
SGR (%/day)	1	$2.34 \pm 0.12$	$1.82 \pm 0.19$	+28.6%
FCR	-	$1.42 \pm 0.08$	$1.78 \pm 0.15$	+20.2% (Lower is better)
Survival Rate	100%	96.0%	88.0%	+9.1%

### TABLE 2: Basil Crop Performance & Nutritional Analysis (65-Day **Growth Cycle**)

Smart System (Mean ± SD)	Conventional (Mean ± SD)	Performance Improvement				
Morphological & Biomass						
$38.6 \pm 2.8$	$27.4 \pm 3.9$	+40.9%				
$142.8 \pm 11.2$	99.6 ± 15.4	+43.4%				
$18.7 \pm 1.4$	$13.2 \pm 1.9$	+41.7%				
Physiological						
$42.6 \pm 2.1$	$36.8 \pm 3.4$	+15.8%				
$18.4 \pm 1.2$	$14.6 \pm 1.8$	+26.0%				
Nutritional Quality						
$4.82 \pm 0.23$	$3.96 \pm 0.34$	+21.7%				
$0.48 \pm 0.04$	$0.39 \pm 0.06$	+23.1%				
$3.74 \pm 0.18$	$3.12 \pm 0.28$	+19.9%				
	## SD)  Orphological & Biomass	orphological & Biomass $ 38.6 \pm 2.8 $ $ 27.4 \pm 3.9 $ $ 142.8 \pm 11.2 $ $ 99.6 \pm 15.4 $ $ 18.7 \pm 1.4 $ $ 13.2 \pm 1.9 $ Physiological $ 42.6 \pm 2.1 $ $ 36.8 \pm 3.4 $ Nutritional Quality $ 4.82 \pm 0.23 $ $ 3.96 \pm 0.34 $ $ 0.48 \pm 0.04 $ $ 0.39 \pm 0.06$				

## **Conclusion**

- ❖78.4% improvement in water quality stability (94.2% vs. 52.8% time in target range).
- ❖28% faster fish growth and 43.4% higher crop yields compared to conventional systems.
- ❖94.7% accuracy in early disease detection. ❖ Predicts system failures 72 hours in advance with 87% reliability.
- ❖73.3% reduction in daily labor (1.2 vs. 4.5 hours/day).
- ❖35% less water and 21.5% less energy consumed per day.
- ❖ Higher productivity achieved with significantly lower resource input.

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System Performance Metrics