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Optimization of Water Quality in Shrimp-Shallot Aquaponic Systems: A Machine Learning-Integrated IoT Approach

Munirul Ula[1], Muliani[2], and Hafizh Al Kautsar Aidilof[3]

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Abstract: This research presents a pioneering water quality regulation system designed for low salinity shrimp-shallot aquaponics in tropical climates. The system integrates cutting-edge sensor technologies, intelligent feedback loops, and precise parameter adjustments within an IoT framework. It aims to optimize critical water quality parameters, including pH, temperature, salinity, nitrite, and dissolved oxygen, to ensure the health and vitality of shrimp populations while fostering the co-cultivation of shallots. The methodology involves comprehensive model training using Genetic Algorithm on a computer, followed by real-time inference and control through an Arduino microcontroller and dispensing actuators. Thirty days of testing in a tropical aquaponics setup demonstrated the system's effectiveness in maintaining optimal water quality conditions for shrimp and shallot growth. The successful integration of Machine Learning with IoT technology signifies a transformative advancement in shrimp-shallot aquaponics, offering sustainable and intelligent solutions for commercial agriculture in tropical regions. Further scalability, adaptability to diverse climates, and integration of additional water quality parameters are envisaged for future developments, along with the exploration of remote monitoring and sustainability metrics.

Keywords: *Shrimp Aquaponics; Low Salinity Water; Water Quality Regulation; IoT and Machine Learning; Tropical Climate*

1. Introduction

Aquaponics, the innovative integration of aquaculture with hydroponics, has emerged as a compelling response to the global challenges of food scarcity and environmental sustainability[1]–[3]. This synergy leverages the natural relationship between aquatic animals and plants to offer a self-sustaining ecosystem that promotes healthy growth without the use of chemicals or pesticides[4]–[6]. Research has revealed the system's ability to enhance production by ten times, using merely 2–10% of water compared to conventional farming techniques[7], [8]. However, the intricacies of nutrient management, especially in commercial setups involving low salinity water Vannamei shrimp and shallot plants, have not been thoroughly explored.

The application of machine learning (ML) and Internet of Things (IoT) in agriculture marks a significant technological advancement. These technologies offer precise control and automation, potentially revolutionizing traditional farming practices [5], [9]–[11]. From smart monitoring of pH levels and water temperature to precise regulation of nitrite concentrations and dissolved oxygen, IoT has proven its efficacy [12]. Yet, the development of ML-driven methods to control essential nutrients for specific growth such as low salinity water Vannamei shrimp and shallot plants is still a pioneering venture.

[1]*Information Technology, Universitas Malikussaleh, Lhokseumawe - Indonesia*
ORCID ID : 0000-0001-6341-8904
[2] *Aquaculture, Universitas Malikussaleh, Lhokseumawe - Indonesia*
ORCID ID : 0000-0001-8576-1148
[3] *Informatics, Universitas Malikussaleh, Lhokseumawe - Indonesia*
ORCID ID : 0009-0001-0757-7983
** Corresponding Author Email: author@email.com*

Designing an intelligent water quality parameters regulation system in aquaponics is burdened with challenges. Data scarcity poses a significant barrier, necessitating synthetic data generation techniques and novel methodologies [13]–[16]. These challenges are further complicated when applied to unique commercial setups involving Vannamei shrimp and shallot plants.

While previous research has focused on regulating nutrients like calcium and phosphor [5], [17], [18], our work aims to innovate by measuring and regulating essential water quality parameters in aquaponic solutions through a data-driven method. This bold direction could mark a major milestone in commercial cultivation of species like Vannamei shrimp and shallot plants. As aquaponics transitions from small-scale experimental setups to commercial applications, the need for scalable, cost-effective, and efficient models becomes paramount. The fusion of IoT with ML offers an unprecedented opportunity to develop intelligent systems capable of handling complex water quality dynamics, adjusting to seasonal variations in tropical climate. Our research is directed at filling this critical gap, focusing on low salinity water for Vannamei shrimp and shallot plant cultivation.

Shrimp aquaponics' appeal is not merely in its productivity but also in its alignment with environmental sustainability. By minimizing water usage, reducing reliance on synthetic chemicals, and promoting a balanced ecosystem, aquaponics represents a path towards responsible farming. This paper explores the intricate interplay between water quality management and environmental considerations, leveraging ML and IoT to optimize both productivity and sustainability.

One of the most formidable challenges in designing an intelligent system for water quality regulation in low salinity aquaponic systems lies in the deficiency of data. To tackle this problem, researchers have implemented various synthetic data generation techniques. In a significant contribution to this domain, Dhal et al [17] used an iterative approach, generating data samples that matched the desired statistical distribution. They later revised these samples to rectify any logical violations. A step further was taken by Soltana et al [19], who introduced Sensegen, a deep-learning-based architecture for synthesizing sensory data, comprising LSTM networks and MDNs. This approach was further evolved by Romanelli et al [20], who presented SynSys, an ML-based synthetic data generation technique that leverages nested sequences using Markov models. The utilization of Monte-Carlo approaches to synthetic data generation, focusing on generating mean and covariance matrices between classes, was elucidated in [21], [22].

The subsequent regulation of the water quality parameters selected through these methods using an IoT-based setup forms a critical step towards automating the symbiotic growth conditions of plants and fish in aquaponic systems. Notable research in this sphere includes Roychowdhury's [23] proposal of a smart irrigation system, Chhabada et al.'s solar powered real-time monitoring with cloud integration[24], Zulkarnaen's [25] dual mode solar power for iot based smart farming system, and similar initiatives by Alsammak et al. [26] and Devendra [27]. Unlike these research works, our research uniquely focuses on the monitoring and regulation of vital water quality parameters in the shrimp-shallot aquaponic, leveraging data-driven methodologies rather than regulating chemical properties.

This study presents a pioneering effort to align IoT and ML, aiming to create an adaptive system for optimizing water quality in low salinity in Vannamei shrimp aquaponic operations with shallot plants. The research includes:

- Development of a data-driven methodology for water quality monitoring and regulation.
- Exploration of synthetic data generation tailored for aquaponic systems.
- Integration of IoT and ML to formulate a cohesive, adaptive system for water quality monitoring and regulation in shrimp-shallot aquaponic system.

The unique contribution of this paper stands at the intersection of technology and agriculture, offering an advanced, context-aware system that could revolutionize commercial aquaponics.

2. Material and Method

The methodology of this research involved the analysis and integration of data, generation of synthetic data, feature selection, and the creation of an IoT system specifically designed for the concurrent cultivation of Vanamei shrimp and shallot using low salinity water. The following subsections detail the various aspects of the methodology. The detailed setups of the shrimp ponds and plant beds are illustrated in Figure 1.

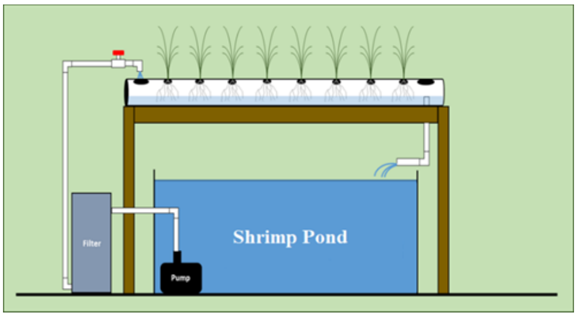

Fig. 1. The setups of the shrimp-shallot aquaponics

2.1. Data Collection and Analysis

The dataset was gathered over six months period from three aquaponic experimental tarpaulin ponds setup in aquaculture laboratory, Universitas Malikussaleh, Aceh, Indonesia. This aquaponics platform was designed to cultivate shrimp and shallot using low salinity water. The data was collected daily from three tarpaulin ponds breeding shrimp and from greenhouse cultivating shallots. The dataset comprised 180 observations and 6 variables, which are pH, temperature, Dissolve Oxygen, salinity, nitrate concentration and shrimps and shallot biomass.

2.2. Generation of Synthetic Data

Due to the limited size of the dataset, two variations of Monte-Carlo (MC) approaches were applied to generate synthetic data. This enabled the creation of representative samples for robust analysis. The detail data synthesis process are as follows: defining suitable distributions for each variable, considering the original dataset's attributes, implementing Monte Carlo simulations to generate synthetic data, and maintaining observed correlations among variables. This process performs verification the synthetic dataset's fidelity, compare key statistics, distributions, and correlations, evaluate how synthetic data responds to variations in distribution parameters and assess the synthetic data's robustness in response to parameter changes. As the result of this process, it combines the original 180-entry dataset with the synthetically generated one, creating a consolidated dataset of 10000 entries for enhanced statistical analysis. The synthetics data generation was conducted using phyton programing as follows:

```
import numpy as np

original_data = aquaponic.xlsx

non_constant_vars = np.std(original_data, axis=0) != 0

filtered_data = original_data[:, non_constant_vars]
```

```
num_synthetic_points = 10000

num_samples, num_features = filtered_data.shape

synthetic_data = np.zeros((num_synthetic_points,
num_features))

# Performing Monte Carlo-based synthetic data generation

for i in range(num_synthetic_points):

    # Randomly sample from the original data

    random_indices = np.random.randint(0, num_samples,
size=num_features)

    synthetic_data[i] =
filtered_data[random_indices].mean(axis=0)

# dividing the iterations among multiple CPU cores

import multiprocessing

def generate_synthetic_data_parallel(start, end, result):

    for i in range(start, end):

        random_indices = np.random.randint(0,
num_samples, size=num_features)

        result[i - start] =
filtered_data[random_indices].mean(axis=0)

num_cores = 4

pool = multiprocessing.Pool(processes=num_cores)

split_indices = np.linspace(0, num_synthetic_points,
num_cores + 1, dtype=int)

results = []

for i in range(num_cores):

    result = np.zeros((split_indices[i + 1] - split_indices[i],
num_features))

    results.append(result)

for i in range(num_cores):

    pool.apply_async(generate_synthetic_data_parallel,
(split_indices[i], split_indices[i + 1], results[i]))

pool.close()

pool.join()

synthetic_data = np.vstack(results)
```

2.3. The Design of IoT System Aquaponics Water Quality Monitoring and Regulation

To establish an IoT system for monitoring and regulating water quality in shrimp aquaponics systems, the entire system was segmented into three key components: (a) the sensor subsystem, (b) the feedback loop, and (c) the actuator system. The sensor subsystem encompasses various water quality sensors designed to measure and transmit data related to essential parameters, such as pH, temperature, dissolved oxygen (DO), nitrite levels, and salinity, to an Arduino controller. Some consideration was given to sensor selection, weighing factors such as cost, accuracy, interface compatibility, and ease of integration.

These sensors interface seamlessly with Arduino devices and are programmed using Arduino's integrated development environment (IDE). Calibration of these sensors involves rinsing with distilled water. Each sensor collects multiple data points, averaging the results, and relaying the values in the appropriate units.To effectively monitor and regulate the water quality parameters throughout the aquaponics system, a feedback loop was implemented to continuously assess the water quality parameters. This feedback loop interfaces with both the sensor subsystem and actuator system to gather real-time water quality data and, if necessary, administer corrective actions. The feedback loop is developed in C++ for Arduino's IDE, leveraging libraries designed for these water quality sensors. Since the sensors lack native serial communication, a digital pin connection is employed. Using Arduino enables the creation of highly modular and object-oriented code for ease of debugging and future enhancements. An Arduino board, equipped with multiple pin connections, serves as the controller for this program. The feedback loop initiates by initializing all connected components, including the water quality sensors and actuators. After a successful setup sequence, the loop continuously samples data from the water quality sensors, averaging the measurements to determine the current water quality parameters. If the measured levels fall below the desired thresholds, the actuator system is signalled via the Arduino's GPIO pins to perform a single cycle of corrective action, incrementally adjusting the concentration of the specified parameter. This iterative approach ensures that the system maintains its target goals while minimizing the risk of oversaturation or undersaturation, compared to making large, sudden corrections.

2.4. Integration of Machine Learning in Regulating System

As a complement to this system, a machine learning based Genetic Algorithm model can be integrated to regulate water quality parameters in aquaponics. However, due to the limited computational resources and memory constraints of most Arduino boards, training a Genetic Algorithm model directly on the Arduino is challenging. Therefore, a two-step process is adopted, involving a more capable computer for running GA prediction and an Arduino IDE for inference and control.

The optimization process maximizes the growth of shrimp and shallots by combining genetic algorithms and machine learning. The steps for obtaining optimal water quality parameters for shrimp and shallots growth as follows:

- Two essential Python libraries for machine learning and genetic algorithm optimization are imported: Scikit-learn and DEAP.
- Measurements of the growth of shallots and shrimp as well as characteristics of the water quality are included in a synthetic dataset.
- Target variables and input features are extracted as part of the dataset processing.
- Training and testing sets of data are separated apart.
- Five. Independent Random Forest To anticipate the growth of shrimp and shallots, regression models are used.
- Mean squared error (MSE) is used to evaluate the performance of the model.
- DEAP is used to configure the genetic algorithm; factors such as population size, algorithm settings, and optimization bounds are set.

The Phyton code for the optimization process as follows:

```
python
import random
import numpy as np
import pandas as pd
from deap import base, creator, tools, algorithms
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
data = pd.read_csv('aquaponics.csv')
X = data[['Salinity', 'DO', 'pH', 'Temperature']].values
y_shrimp = data['ShrimpGrowth'].values
y_shallot = data['ShallotGrowth'].values
# Split the data into training and testing sets
X_train, X_test, y_shrimp_train, y_shrimp_test,
y_shallot_train, y_shallot_test = train_test_split(X,
y_shrimp, y_shallot, test_size=0.2, random_state=42)
# Train the machine learning models
shrimp_model =
RandomForestRegressor(n_estimators=100,
random_state=42)
shrimp_model.fit(X_train, y_shrimp_train)
shallot_model =
RandomForestRegressor(n_estimators=100,
random_state=42)
shallot_model.fit(X_train, y_shallot_train)

# Evaluate the models on the test data
shrimp_predictions = shrimp_model.predict(X_test)
shallot_predictions = shallot_model.predict(X_test)


shrimp_mse = mean_squared_error(y_shrimp_test,
shrimp_predictions)
shallot_mse = mean_squared_error(y_shallot_test,
shallot_predictions)


print(f"Shrimp Model MSE: {shrimp_mse}")
print(f"Shallot Model MSE: {shallot_mse}")


# Define the optimization problem
creator.create("FitnessMulti", base.Fitness, weights=(1.0,
1.0))
creator.create("Individual", list,
fitness=creator.FitnessMulti)
num_parameters = 4
parameter_bounds = [(0, 10), (5, 10), (7, 9), (25, 30)]
# Genetic Algorithm parameters
population_size = 10000
generations = 50
crossover_prob = 0.7
mutation_prob = 0.2
# Fitness function
shrimp_growth_prediction =
shrimp_model.predict([params])
shallot_growth_prediction =
shallot_model.predict([params])
return shrimp_growth_prediction,
shallot_growth_prediction
# toolbox functions
toolbox = base.Toolbox()
toolbox.register("attr_float", random.uniform,
parameter_bounds[0][0], parameter_bounds[0][1])
toolbox.register("individual", tools.initCycle,
creator.Individual, (toolbox.attr_float,),
n=num_parameters)
toolbox.register("population", tools.initRepeat, list,
toolbox.individual)
```

```
toolbox.register("evaluate", evaluate)

toolbox.register("mate", tools.cxTwoPoint)

toolbox.register("mutate", tools.mutGaussian, mu=0, sigma=1, indpb=0.2)

toolbox.register("select", tools.selNSGA2)

# Create the initial population

population = toolbox.population(n=10000)

# Run the genetic algorithm

algorithms.eaMuPlusLambda(population, toolbox, mu=population_size, lambda_=population_size, cxpb=crossover_prob, mutpb=mutation_prob, ngen=generations, stats=None, halloffame=None, verbose=True)

pareto_front = tools.sortNondominated(population, len(population), first_front_only=True)[0]

print("Optimal Solutions (Parameter Values):")

for ind in pareto_front:

    print(ind.fitness.values)
```

The outcomes of this phyton code provide a range of parameter sets with practical application possibilities for enhancing the growth of shrimp and shallots.

2.5. Arduino IDE code

This model inputting relevant water quality parameters, such as pH, temperature, salinity, nitrite, DO, shrimp biomass and shallot biomass into the model to make predictions. The Arduino IDE, equipped with the trained model, is deployed within the aquaponics system. Real-time monitoring ensures that the model's predictions align with the desired water quality control objectives. This integrated approach combines advanced Genetic Algorithm modeling with the Arduino-based water quality monitoring and control system, optimizing the harvested yield of shrimp and shallot in the aquaponics environment.

```
#include <aquaponic.h>

const int controlPin = 5;

float predictedSalinity = 0;

float predictedDO = 0;

float predictedpH = 0;

float predictedTemperature = 0;

void setup() {

  pinMode(controlPin, OUTPUT);

  }

void loop() {

  float salinityValue = analogRead(A0);

  float DOValue = analogRead(A1);

  float pHValue = analogRead(A2);

  float temperatureValue = analogRead(A3


  predictedSalinity = receivePredictedValue("Salinity");

  predictedDO = receivePredictedValue("DO");

  predictedpH = receivePredictedValue("pH");

  predictedTemperature = 
receivePredictedValue("Temperature");


  if (salinityValue < predictedSalinity) {

     digitalWrite(controlPin, HIGH);

  } else {

    digitalWrite(controlPin, LOW);

  }


delay(1000);

}

float receivePredictedValue(String parameter) {

predicted values for the specified parameter

    float value = 0;

  return value;

}
```

3. Result and Discussion

3.1. Research Process

The analytical process from the dataset is systematically depicted in Figure 2. This pipeline, designed with meticulous consideration, encapsulates the multifaceted approach employed to develop the water quality regulation and IoT-based actuation within aquaponic systems.

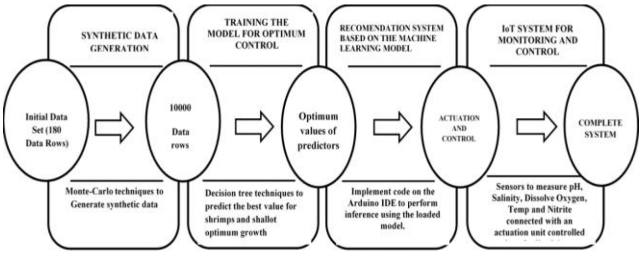

Fig. 2. The pipeline of regulating water quality in aquaponic environments.

3.2. Data Pre-processing and Synthetic Data Generation

Before commencing the in-depth analysis, a preliminary phase of data refinement was conducted with great attention to detail. After completing the initial phase, the dataset's dimensions and analytical capabilities were enhanced through the application of synthetic data generation techniques within the respective domain. The deliberate decision was made to avoid the use of standardization or normalization procedures due to the inherent normal distribution observed in all predictors. Using a Monte Carlo methodology, a meticulous process was undertaken to generate synthetic data point. The complex augmentation process reached its culmination with the creation of a comprehensive dataset consisting of 10,000 observations. Due to the computationally demanding nature of synthetic data generation and feature selection, a resilient computational infrastructure was necessary for their orchestration. For this purpose, a computational computer cluster equipped with 4 workstations with Intel(R) Core (™) i5 processor and 16 GB of memory was utilized, providing the necessary computational power needed for conducting this complex analytical task.

3.3. Prototype of A Monitoring and Control System for Water Quality

In order to implement an Internet of Things (IoT) system for the purpose of monitoring and regulating water quality in aquaponics systems for low salinity shrimp, the complete system was divided into three fundamental elements: (a) the actuator system; (b) the feedback loop; and (c) the sensor subsystem. The sensor subsystem is comprised of a variety of purpose-built water quality sensors, including those for measuring salinity, pH, dissolved oxygen (DO), nitrite concentrations, and temperature. The information is subsequently conveyed to an Arduino controller. The hardware setup for regulating water quality as shown in Figure 3.

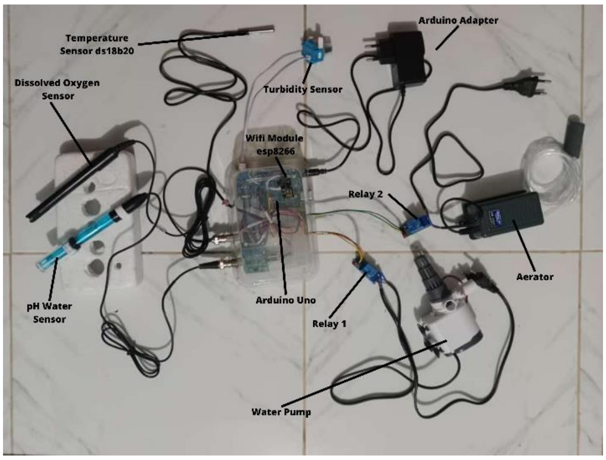

Fig 3. Prototype of a monitoring and control system for water quality

A comprehensive evaluation was conducted during the sensor selection process, wherein numerous factors were considered such as affordability, precision, interface compatibility, and simplicity of integration. The water quality sensors that have been chosen possess the ability to accurately quantify various parameters such as salinity, temperature, dissolved oxygen (DO), and nitrite concentrations. Furthermore, these sensors are designed to be compatible with Arduino controllers. These sensors, as opposed to their counterparts, demonstrate a smooth interface with Arduino devices and are developed using the integrated development environment (IDE) provided by Arduino. The calibration procedure for these sensors involves the application of distilled water for the purpose of purification. Each sensor collects a multitude of data points, computes the mean of these calculations, and then transmits the values in the appropriate units of measurement.

In order to provide efficient regulation of water quality parameters inside the aquaponics system, a feedback loop was established to consistently evaluate the prevailing water conditions. The feedback loop establishes a connection between the sensor subsystem and actuator system, enabling the collection of real-time data on water quality. Additionally, it facilitates the implementation of corrective measures. The feedback loop is implemented in Arduino IDE. The feedback loop is initiated by initializing all interconnected elements, which encompass the water quality sensors and actuators.

Following a proficient initialization process, the iterative loop consistently acquires data from the sensors responsible for monitoring water quality. These measurements are subsequently averaged to ascertain the prevailing parameters pertaining to the quality of the water. In the event that the measured levels are found to be lower than the acceptable thresholds, the actuator system is notified through the GPIO pins of the Arduino. This notification prompts the actuator system to execute a solitary cycle of corrective action, gradually modifying the concentration of the specified parameter. The utilization of an iterative strategy in this context guarantees the system's ability to uphold its desired objectives, while simultaneously mitigating the potential for excessive or insufficient saturation, as opposed to implementing significant and abrupt adjustments.

In this particular scenario, the actuator subsystem consists of a PIC microprocessor, motor modules that can tolerate 12 V, and two 12 V stepper motors used for nutrient dispensing. The stepper motors are connected to the motor modules, which provide both electrical power and rotational control signals to the motors. The motor modules are interconnected with the PIC microcontroller, which is responsible for determining the direction and speed of motor rotation. The initiation of motor operation is dependent on the reception of a signal from the Arduino, which signifies the requirement for nutrient correction within the aquaponics system.

3.4. Aquaponics Water Quality Monitoring and Control Mechanism

The integration of these multifaceted components culminated in an innovative, IoT-based water quality regulation system. This cohesive design, illustrated in Figure 4, comprised three main subsystems, each contributing to the system's holistic function.

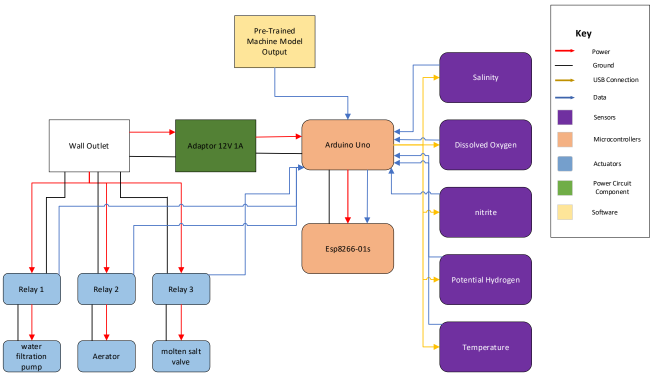

Fig 4. Detailed block diagram of the IoT-based monitoring and dispensing system.

3.5. Genetic Algorithm Data Prediction

This section presents the results and system testing outcomes for a cutting-edge aquaponics water quality regulation system, tailored specifically for shrimp and shallot cultivation. This comprehensive system encompasses the monitoring and control of essential water quality parameters, including pH, temperature (Temp), salinity, nitrite, and dissolved oxygen (DO). The system integrates state-of-the-art sensors, actuators, and machine Generic Algorithm to optimize water quality conditions for optimal shrimp growth. By fusing the insights drawn from advanced machine learning techniques with real-world sensing and actuation, this system emerges as a trailblazer in automating and optimizing commercial aquaponic setups. Such advancements are likely to revolutionize the way in which aquaponic systems are monitored and controlled, opening new horizons for sustainable agricultural practices.

The initial subsystem of the aquaponics system focuses on monitoring water quality parameters, a pivotal component in ensuring the well-being of shrimp. To measure the concentration of critical parameters such as pH, Temp, nitrite, salinity, and dissolved oxygen, a suite of sensors is deployed. These sensors are strategically positioned to allow precise sampling of water quality parameters. The system operates by providing the sensors with a minimum of 30 minutes to accumulate data on the current parameter concentrations. The collected water quality parameters data are then seamlessly communicated through a digital and analog pint to a central control unit, the Arduino Uno. The heart of the water quality regulation system lies in its feedback loop, which serves as the bridge between the sensor and actuator systems. A Python-based Genetic Algorithm analyzing synthetic historical data to predict the optimum water quality parameters, the predicted optimum water quality parameters as shown Table 1.

Table 1. Predicted optimum water quality parameters

Trial	Salinity (ppt)	DO (mg/L)	pH	Temp (°C)	Shrimp Growth	Shallot Growth
1	10	8.0	7.0	30	High	High
2	5	6.5	7.5	28	Medium	High
3	15	7.5	6.8	32	High	Low
4	8	9.0	7.2	26	Medium	Medium
5	12	6.0	7.8	29	Low	High

The final pivotal component of the system encompasses Nema 17 stepper motor actuators, responsible for the precise dispensing of corrective agents. These actuators are activated solely in response to a high signal received from the Arduino Uno, signaling the microcontroller to initiate the actuators. The actuators drive the adjustment process by precisely regulating parameter-altering mechanisms, such as chemical dosing, water flow rates and on/off electric supply. This fine-tuned control continues until the water quality parameters reach stable and optimal levels.

3.6. Experimental IoT System Testing

The system that utilizes the Internet of Things (IoT) and employs Machine Learning based on Genetic Algorithm was tested aims to substantiating the effectiveness of the system. Table 2 presents the outcomes of numerous experimental trials conducted within a 0.5 m x 1.5 m x 3 m shrimp aquaponic shallot system, spanning from 1 September 2023 to 1 October 2023. The stock density of shrimp was 100 per meter cubic.

The system testing phase, conducted over a period of one months, yielded insightful observations in Table 2 that emphasis the efficiency and precision of the aquaponic water quality regulation system. The subsequent test runs demonstrated the system's efficacy in maintaining optimal water quality parameter levels. From the testing result, its demonstrations, the proposed system achieved desired water quality parameter concentrations.

Table 2. The testing of water quality of aquaponic in laboratory

Date	Adjusted Parameters	pH	Temp (°C)	Nitrite (ppm)	Sal. (ppt)	DO (ppm)	Observations
September 1, 2023	pH, Temp, NO2, Salinity, DO	7.3	28	0.12	6.0	6.5	Initial parameter adjustment, five-cycle process
September 2, 2023	pH, Temp, NO2, Salinity, DO	7.4	28.5	0.11	6.2	6.6	Continued parameter regulation
September 3, 2023	pH, Temp, NO2, Salinity, DO	7.6	29	0.10	6.4	6.7	Adjustment for optimal water quality
September 4, 2023	-	7.9	29.5	0.09	6.6	6.8	Desired parameter levels achieved earlier
September 5, 2023	-	8.1	30.0	0.08	6.8	6.9	Efficient parameter control and regulation
September 6, 2023	-	8.3	30.2	0.07	7.0	7.0	System optimally maintains parameter levels
September 7, 2023	-	8.5	30.4	0.06	7.2	7.1	Consistent water quality parameter control
September 8, 2023	-	8.6	30.6	0.05	7.4	7.2	Precise parameter adjustments
September 9, 2023	-	8.4	30.8	0.04	7.6	7.3	Stable and optimal parameter levels
September 10, 2023	-	8.2	31.0	0.03	7.8	7.4	Sustained water quality control
September 11, 2023	-	8.0	31.2	0.02	8.0	7.5	Continued efficient parameter regulation
September 12, 2023	-	7.8	31.4	0.01	8.2	7.6	System maintains optimal parameters
September 13, 2023	-	7.6	31.6	0.02	8.4	7.7	Consistent water quality regulation
September 14, 2023	-	7.5	31.8	0.03	8.6	7.6	Parameters within desired ranges
September 15, 2023	-	7.7	32.0	0.04	8.8	7.5	Precise adjustments for water quality
September 16, 2023	-	7.9	32.2	0.05	9.0	7.4	Stable and optimal parameter levels
September 17, 2023	-	8.1	32.4	0.06	9.2	7.3	Parameter control remains efficient
September 18, 2023	-	8.3	32.6	0.07	9.4	7.2	Continued maintenance of optimal parameters
September 19, 2023	-	8.5	32.8	0.08	9.6	7.1	Consistent water

Date	Adjusted Parameters	pH	Temp (°C)	Nitrite (ppm)	Sal. (ppt)	DO (ppm)	Observations
							quality regulation
September 20, 2023	-	8.6	33.0	0.09	9.8	7.0	Parameters maintained within desired ranges
September 21, 2023	-	8.4	32.9	0.10	10.0	6.9	Precise adjustments for water quality
September 22, 2023	-	8.2	32.7	0.11	10.2	6.8	Stable and optimal parameter levels
September 23, 2023	-	8.0	32.5	0.12	10.4	6.7	Parameter control remains efficient
September 24, 2023	-	7.8	32.3	0.11	10.6	6.6	Continued maintenance of optimal parameters
September 25, 2023	-	7.6	32.1	0.10	10.8	6.5	Consistent water quality regulation
September 26, 2023	-	7.5	31.9	0.09	11.0	6.4	Parameters maintained within desired ranges
September 27, 2023	-	7.7	31.7	0.08	11.2	6.3	Precise adjustments for water quality
September 28, 2023	-	7.9	31.5	0.07	11.4	6.2	Stable and optimal parameter levels
September 29, 2023	-	8.0	31.3	0.06	11.6	6.1	Parameter control remains efficient
September 30, 2023	-	8.2	31.1	0.05	11.8	6.0	Continued maintenance of optimal para

From the result, the pH levels ranged from 7.3 to 8.6, the temperature ranged from 28°C to 33°C. The data shows that the pH and temp was initially adjusted and gradually stabilized within the desired range. The pH levels in the aquaponics system are crucial because they affect the overall health of both the aquatic animals and plants. Moreover, the temperature is an important factor that impacts the metabolic rates of fish and plant growth. In this system. Nitrite concentration is a critical parameter to monitor as high levels can be harmful to shrimp. The data shows that the nitrite levels started at 0.12 ppm and gradually decreased to 0.05 ppm over the course of the month, indicating efficient parameter control.

Salinity and dissolved oxygen are critical parameters, particularly when it comes to aquaponic systems that utilize shallot and vanname shrimp. The salinity levels within this system varied between 6.0 ppt and 11.8 ppt. According to the data, adjustments were made to salinity levels, which were then stabilized within the intended range. The DO concentrations varied between 6.5 and 7.7 ppm. The system consistently maintained oxygen levels within the intended range, as evidenced by these values. The "Observations" column provides contextual information for each date, detailing the objective or result of the parameter modifications. As evidenced by these observations, the system was adequately maintained and modifications were implemented to guarantee the highest quality of water. The system consistently attained and sustained the intended levels of parameters.

In conclusion, the September 2023 data from this aquaponics monitoring system indicates that the system was effectively maintained and regulated throughout the month. To maintain ideal water quality—critical for the well-being and development of plants and fish within the aquaponics system—various parameters including temperature, nitrite concentrations, salinity, and dissolved oxygen were regulated and modified. Achieving the intended ranges and maintaining consistent parameter control are indications of the monitoring and adjustment procedure's effectiveness. This result highlights the system's capability to regulate water quality parameters in a shrimp-shallot aquaponic system, ensuring that the aquaponic environment consistently meets the desired parameter thresholds. By means of one-month testing, the shrimp-shallot aquaponics water quality regulation system demonstrates itself to be an effective and sophisticated method for optimizing shrimp aquaponics water quality parameters. Through the utilization of sophisticated sensors, intelligent feedback loops, and accurate parameter adjustments, the system guarantees the preservation of critical water quality parameters at ideal levels, which contributes to the growth and health of shrimp within the aquaponic setting. For implementation in the actual world, additional field testing and validation is recommended.

The successful completion of the tests serves as evidence of the stability and accuracy of this novel methodology. This underscores the potential of combining Internet of Things (IoT) and Machine Learning to develop intelligent and sustainable solutions for aquaponic environments, representing a significant progression in the field of commercial agriculture.

3.7. Discussion

The main goal of this methodology's development is to establish a recommendation system that incorporates sensing and actuation components that operate in real time. The objective of this system is to control a range of water quality parameters present in the aquaponic solution, including pH, Temperature (Temp), Salinity, Nitrite, and Dissolved Oxygen. Attaining ideal growth conditions for shrimp and shallot plants in a unified system is the ultimate objective. In order to achieve this goal, a methodology was devised through the examination of pre-existing observations taken from the historical dataset.

This research paper introduces a novel methodology in the domain of aquaponics: the integration of shallots and shrimp aquaponics under low salinity conditions; in this system, both species are cultivated concurrently. By enabling the co-cultivation of two distinct organisms in a shared habitat, this innovative approach has substantial potential to increase resource utilization and production, thereby enhancing efficiency and sustainability in aquaponics. A novel strategy that expands the range of aquaponic systems and establishes a unique foundation for the progression of sustainable, integrated agriculture is the incorporation of shallots and low salinity shrimp. Furthermore, it is significant that machine learning was implemented as a method of control and inference on the Arduino microcontroller in this research. The integration of machine learning algorithms into the control mechanism of the aquaponics system facilitates instantaneous decision-making and accurate management of water quality parameters. The utilization of this sophisticated technology not only amplifies the overall efficacy of the system, but also plays a pivotal role in fostering the sustainability and expandability of aquaponic activities.

One notable benefit of employing a data-driven Internet of Things (IoT) system in contrast to a conventional aquaponic system is the potential for cost reduction achieved by enhancing crop output and produce quality through the incorporation of artificial intelligence (AI) technologies. Therefore, there is a substantial financial gain derived from the aquaponic system. An additional approach proposed in this study is the implementation of nutrient reduction strategies to limit the availability of essential elements for plant development.

The focus of this study is to optimize water quality parameters (pH, temperature, salinity, nitrite, and dissolved oxygen) consistently throughout the year, irrespective of the prevailing tropical climate conditions. The regulation of Nitrite concentration is crucial in maintaining water quality and pH levels in a solution, as it serves as a significant determinant. By addressing imbalances in the solution, the control of Nitrite concentration effectively mitigates potential concerns. In addition, the level of Dissolved Oxygen concentration significantly influences the well-being of shrimp. Consequently, the implementation of an Internet of Things (IoT)-enabled sensing and actuation system for the regulation of water quality parameters is essential in order to effectively manage the environment and facilitate the optimal growth and productivity of both shrimp and crop plants within a unified framework. The primary benefit of using this automated system is in its ability to significantly decrease the financial burden associated with rectifying unregulated aquaponic systems affected by complications arising from excessive buildup of water quality indicators. Another benefit of the system is the decrease in the quantity of water quality parameters that are monitored in commercial aquaponic systems. With the exception of the aforementioned improvements in productivity and size of the food, the present study has identified some notable advantages in our controlled aquaponic system when compared to existing commercial operations.

4. Conclusion and Future Research

4.1. Conclusion

The proposed IoT system effectively controlled and preserved important water quality parameters through September 2023. The well-being of shrimp and shallot plants was promoted by the constant adjustment and control of parameters such as pH, temperature, nitrite levels, salinity, and dissolved oxygen, all of which stayed within the intended ranges. Shrimp and shallot growth were impacted by the initial adjustment and progressive stabilization of pH levels, which ranged from 7.3 to 8.6. The ideal temperature range, which influenced metabolic rates and overall system health, was maintained between 28°C and 33°C. The nitrite concentration maintained at 0.12 ppm to 0.05 ppm, demonstrating effective parameter management and lowering the risk of injury to the shrimp population. Salinity levels ranging from 6.0 ppt to 11.8 ppt and dissolved oxygen ranging from 6.5 ppm to 7.7 ppm were successfully maintained during the testing period. The stability of the aquaponic environment was preserved through an automated feedback loop that accurately assessed the water conditions. The outcomes demonstrate how the system's machine learning and IoT integration capabilities may transform aquaponic monitoring and control, promoting sustainability and commercial aquaponics. Therefore, the study's findings highlight how well the system controls many aspects of water quality, providing aquaponics with a novel and exciting option. Its practical potential will be ascertained by more field testing and validation, but the preliminary results are positive for the development of sustainable agriculture.

4.2. Future Research

Adaptation to Diverse Seasons: this aspect is of utmost importance as it dictates the system's resilience and suitability across different climates and geographic areas, thereby enhancing its versatility and adaptability to practical circumstances, particularly in areas characterized by fluctuating tropical seasons, including periods of both rain and drought.

Commercial-Scale Implementation: It is critical to assess the performance and economic feasibility of the system in a commercial setting in order to ascertain its practical implications and capacity to bring about a paradigm shift in the aquaponics sector.

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Author contributions

Munirul Ula: Conceptualization, Methodology, Software, Field study **Hafizh Al Kautsar Aidilof:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Muliani:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] K. Taji, A. Sohail, F. Ghanimi, I. Ghanimi, S. ilyas, and Y. T. Ahmad, "A Systematic Literature Review of Computational Studies in Aquaponic System," International Journal of Advanced Computer Science and Applications, vol. 14, no. 9, 2023, doi: 10.14569/ijacsa.2023.0140936.

[2] V. M. Jothiprakash and M. V. Sezhian, "Nanocomposites based Aquaponic Cropping System Design and Control for Agriculture Industry," International Journal of Scientific Methods in Engineering and Management, vol. 01, no. 04, pp. 12–22, 2023.

[3] P. Kumar, P. Tiwari, and U. S. Reddy, "Estimating fish weight growth in aquaponic farming through machine learning techniques," in 2023 3rd International Conference on Intelligent Technologies (CONIT), Jun. 2023. doi: 10.1109/conit59222.2023.10205680.

[4] K. K. Gayam et al., "Imperative Role of Automation and Wireless Technologies in Aquaponics Farming," Wirel Commun Mob Comput, vol. 2022, pp. 1–13, Jun. 2022, doi: 10.1155/2022/8290255.

[5] S. B. Dhal et al., "A Machine-Learning-Based IoT System for Optimizing Nutrient Supply in Commercial Aquaponic Operations," Sensors, vol. 22, no. 9, p. 3510, May 2022, doi: 10.3390/s22093510.

[6] C. S. Arvind, R. Jyothi, K. Kaushal, G. Girish, R. Saurav, and G. Chetankumar, "Edge Computing Based Smart Aquaponics Monitoring System Using Deep Learning in IoT Environment," in 2020 IEEE Symposium Series on Computational Intelligence (SSCI), Dec. 2020.

[7] F. L. Valiente et al., "Internet of Things (IOT)-Based Mobile Application for Monitoring of Automated Aquaponics System," in 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), Oct. 2018. doi: 10.1109/hnicem.2018.8666439.

[8] C. S. Arvind, R. Jyothi, K. Kaushal, G. Girish, R. Saurav, and G. Chetankumar, "Edge Computing Based Smart Aquaponics Monitoring System Using Deep Learning in IoT Environment," in 2020 IEEE Symposium Series on Computational Intelligence (SSCI), Dec. 2020.

[9] S. Akshay and T. K. Ramesh, "Efficient Machine Learning Algorithm for Smart Irrigation," in 2020 International Conference on Communication and Signal Processing (ICCSP), Oct. 2020.

[10] U. Arora, S. Shetty, R. Shah, and D. K. Sinha,

"Automated Dosing System in Hydroponics with Machine Learning," in 2021 International Conference on Communication information and Computing Technology (ICCICT), Jun. 2021.

[11] L. S. Kondaka, R. Iyer, S. Jaiswal, and A. Ali, "A Smart Hydroponic Farming System Using Machine Learning," in 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Jan. 2023.

[12] U. Arora, S. Shetty, R. Shah, and D. K. Sinha, "Automated Dosing System in Hydroponics with Machine Learning," in 2021 International Conference on Communication information and Computing Technology (ICCICT), Jun. 2021.

[13] H. Jaiswal, K. R. P, R. Singuluri, and S. A. Sampson, "IoT and Machine Learning based approach for Fully Automated Greenhouse," in 2019 IEEE Bombay Section Signature Conference (IBSSC), Oct. 2019. doi: 10.1109/ibssc47189.2019.8973086.

[14] H. K. Srinidhi, H. S. Shreenidhi, and G. S. Vishnu, "Smart Hydroponics system integrating with IoT and Machine learning algorithm," in 2020 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Nov. 2020.

[15] M. A. A. Ahmed and S. M. Reddy, "Smart Hydroponic System and Monitoring of Plants Health through Machine Learning," Int J Res Appl Sci Eng Technol, vol. 11, no. 6, pp. 4261–4263, Jun. 2023.

[16] M. A. A. Ahmed and S. M. Reddy, "Smart Hydroponic System and Monitoring of Plants Health through Machine Learning," Int J Res Appl Sci Eng Technol, vol. 11, no. 6, pp. 4261–4263, Jun. 2023.

[17] S. B. Dhal, M. Bagavathiannan, U. Braga-Neto, and S. Kalafatis, "Can Machine Learning classifiers be used to regulate nutrients using small training datasets for aquaponic irrigation?: A comparative analysis," PLoS One, vol. 17, no. 8, p. e0269401, Aug. 2022, doi: 10.1371/journal.pone.0269401.

[18] M. Lavanaya and R. Parameswari, "Soil Nutrients Monitoring For Greenhouse Yield Enhancement Using Ph Value with Iot and Wireless Sensor Network," in 2018 Second International Conference on Green Computing and Internet of Things (ICGCIoT), Oct. 2018. doi: 10.1109/icgciot.2018.8753083.

[19] G. Soltana, M. Sabetzadeh, and L. C. Briand, "Synthetic data generation for statistical testing," in 2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE), Oct. 2017.

[20] F. Romanelli and F. Martinelli, "Synthetic Sensor Data Generation Exploiting Deep Learning Techniques and Multimodal Information," IEEE Sens Lett, vol. 7, no. 7, pp. 1–4, Oct. 2023.

[21] K. Miok, D. Nguyen-Doan, D. Zaharie, and M. Robnik-Sikonja, "Generating Data using Monte Carlo Dropout," in 2019 IEEE 15th International Conference on Intelligent Computer Communication and Processing (ICCP), Oct. 2019.

[22] R. Guzman, "Monte Carlo Methods on High Dimensional Data," in LatinX in AI at Neural Information Processing Systems Conference 2018, Dec. 2018.

[23] S. Roychowdhury, "Krushi Care: An Integrated Smart Precision Farming App for Enhanced Agricultural Productivity, Profitability and Sustainability," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 9s, pp. 653–660, Jul. 2023, [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/3214

[24] B. Chhabada, V. Narawade, and V. Mane, "Solar-Powered Smart Irrigation System with Cloud Integration," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 10s, pp. 655–659, Aug. 2023, [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/3320

[25] Zulkarnaen, C.-L. Lee, G.-C. Chung, S.-K. Wong, and K.-Y. Chan, "Dual Mode Solar Power for IoT based Smart Farming System," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 8s, pp. 375–380, Jul. 2023, [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/3062

[26] H. N. Alsammak and Z. S. Mohammed, "A Smart IoT-based Automated Irrigation for Farms Using Node MCU (ESP 32F ESP8266 MC) and A Humidity Sensor," International Journal of Intelligent Systems and Applications in Engineering, vol. 10, no. 3s, pp. 237–248, Dec. 2022, [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/2434

[27] V. D. Devendra Singh Mohan Prateek Mishra Priya Singh Alok Srivastav, "IoT Framework for Precision Agriculture: Machine Learning Crop Prediction," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 5s, pp. 300–313, Apr. 2023, [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/2778