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Intelligent Recirculating Aquaculture System of Oreochromis Niloticus: A Feed-Conversion-Ratio-Based Machine Learning Approach

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Abstract*:* Aquaculture has emerged as a critical component in satisfying the world's increasing demand for high-quality protein while relieving strain on wild fish populations. Oreochromis niloticus, also known as Nile tilapia, is one of the most economically important aquaculture species. Optimizing manufacturing efficiency and limiting resource waste, on the other hand, remains a difficulty. The construction of an Intelligent Recirculating Aquaculture System (IRAS) powered by a Feed-Conversion-Ratio (FCR)-based Machine Learning (ML) framework is used in this study to improve the sustainability and productivity of Oreochromis niloticus aquaculture. To establish a closed-loop aquaculture environment, the IRAS incorporates advanced sensor technologies, real-time data monitoring, and control systems. The use of machine learning algorithms trained on historical and real-time FCR data to anticipate and improve the feeding regime for Nile tilapia is central to this approach. The ML model modifies feeding schedules and quantities to enhance growth while decreasing feed waste and the associated environmental effects by continuously learning from FCR patterns. Furthermore, this study shows the feasibility and usefulness of the FCR-based ML strategy in enhancing feed utilization efficiency, growth rates, and overall performance of Oreochromis niloticus in an IRAS through a series of studies. The results show a significant reduction in feed waste and expenses, resulting in improved economic viability and environmental sustainability of the aquaculture system. Furthermore, the ML-driven system adapts to changing environmental conditions and improves the fish population's general health and well-being..

Keywords: *FCR, Multiple Linear Regression, intelligent RAS, Water quality parameters*

1. Introduction

Aquaculture is one of the areas of the global food supply that is growing at the fastest rate and provides people with a source of high-quality protein [1][2][3]. However, the world's population consumes 88% of this continually increasing aquatic output [4].

The demand for aquatic food products is rising because of the expanding global population. The production of capture fisheries has stabilized, and the majority of the prime fishing grounds have reached their limit. In most regions of the world, aquaculture is seen to close the supply and demand gap for aquatic food because catch fisheries will not be able to keep up with the rising global demand for aquatic food [5][6].

In order for the industry to fulfill this promise, many obstacles must be overcome. The sector is intensifying and diversifying, using new species, and changing its methods and procedures, according to key development patterns [3]. Additionally, aquaculture farms and culture-based fisheries in open waters produce less as a result of climate change. It poses a danger to global food security by altering biodiversity, ecosystems, and global fish output by displacing fish stocks from their natural habitats [7].

Advances in automation and intelligent technology have caused aquaculture to develop gradually around the world in a more intensive and intelligent direction. The breeding environment has also gradually changed to a sustainable aquaculture system, greatly increasing aquaculture efficiency [3][7].

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Aquaculture has been impacted by farming organisms, aquaculture habitat, and other changeable factors despite the large number of workers needed. Due to the aforementioned, several concerns with aquaculture include fish nutrition, illness, water contamination, and more. As a component of the third green revolution, intelligent aquaculture will be devoted to resolving issues with fisheries development and increasing aquaculture productivity [3].

Intelligent aquaculture is made possible by high-performance computers and machine learning technologies, which herald a new era for the fishing business. These technologies can also extract high-dimensional qualities and depth information from data [8].

Machine learning, a core component of artificial intelligence, may be learned without requiring extensive programming knowledge and is a crucial technique for creating intelligent decision-making systems. The use of AI in recirculating aquaculture systems increases the precision with which water quality indicators are monitored and presents new ideas for how to slightly reduce energy consumption during breeding [7].

With the gaps in the aquaculture industry presented, this work aims to develop an AI-based model to be used as technological support to enhance the aquaculture industry of the country. Further, through the development of a supervised machine learning technique, this work tries to innovate the current state of tilapia farming in the Philippines, providing technological advancements through an intelligent aquaculture system.

2. Methodology

The RAS was composed of different water tanks and sensors. The Main tank is considered the fish stocking tank. The Detection tank was where the different sensors would be placed. The filtration tank will be composed of mechanical and biological filtering methods. The Water solution tank was where the water stocking tank was ready to be filled in the fish tank. Figure 1 presents the Recirculating Aquaculture System Architectural System.

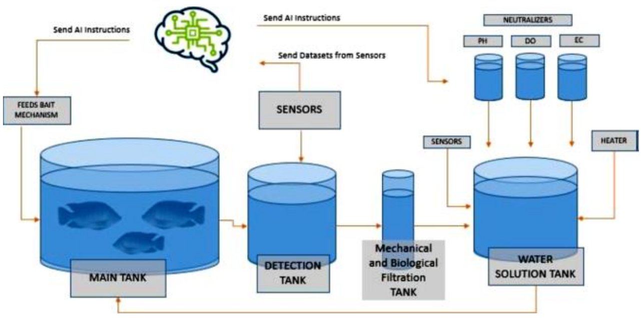

Fig. 1. RAS Architectural System

Table 1 shows the different materials used for building of Recirculating Aquaculture System.

To acquire water quality parameters the study used an Arduino microcontroller device and sensors, the sensors in the microcontroller send the water parameter data to the PC to be evaluated by the system. Listed below are the hardware components that were used in this study.

- Arduino Dissolved Oxygen Sensor
- DFRobot Gravity: analog electrical conductivity sensor/meter (K=10) for Arduino
- PH Meter Sensor Analog Kit
- DHT11 Temperature and Humidity Sensor
- Turbidity Sensor Suspended Turbidity Value Detector Module
- Arduino UNO R3

The hardware component of this study was used to monitor water parameters, which include water dissolved oxygen, Total Dissolved Solid, PH value, and Temperature using the developed microcontroller through the use of sensors. Ammonia is monitored by deriving these parameters using the data obtained from other settings.

Table 1. Material used in RAS

Particular	Specification	Purpose
1 - IBC Water Tank	1000 Liters Capacity 1 x 1 x 1.2 (meters)	Main tank
4 – water container	168 Liters Capacity ordinary	1- Detection, 2- Filtration & 1- Solution Tank
PBC pipe	2 inches	Connect the different tanks
1 - Aerator/ air pump	45 Watts	Generate dissolved Oxygen
1 – submersible waterpump	55 Watts, 3000L per hour	Recirculate water from the solution tank going back tothe Main tank
1 – portable submersible heater	300 watts	To increase the water temperature level
Mechanical & Biological Filtration	Net, pebbles, sand, stone, foam, water purifier lilies	Filter the water from the Main tank

Figure 2. shows the circuit design of the different sensor interfaces used in the development of the system.

Water quality requirements for aquaculture like tilapia, milkfish, and shrimp came from the BFAR office and were validated using previews related research [9][10]11]12].

This study considered indoor fish farming where it used a 1000-liter IBC water storage tank as a pond. It has dimensions of 1m x 1.15m x 1.2m. The pond is connected by PBC pipes to three more water containers namely the detection tank, filtration tank, and solution tank. The setup is considered an intensive culture system for tilapia since the fish was solely dependent on the feed provided and water was closely monitored and maintained.

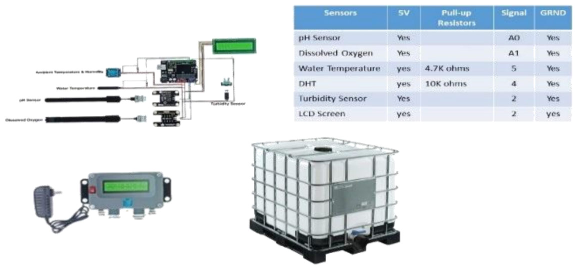

Fig. 2. Sensors Interface

Water ammonia was often altered due to the feeding of cultured fish in fishponds. This impacts aquaculture development and survival, which is why the experiment was monitored frequently. The total ammonia was measured using the pH and temperature data. First calculate the pKa, which is the ionization constant of the ammonium ion. To calculate the pKa value the researcher used the below equation:

$$pKa = 0.0901821 + \frac{2729.92}{T\,°C + 273.2} \qquad (1)$$

Where T= temperature in Degree Celsius.

To compute the fraction of NH3 or Ammonia, the equation below was used:

$$NH3 = \frac{1}{(10(pKa - pH) + 1} \qquad (2)$$

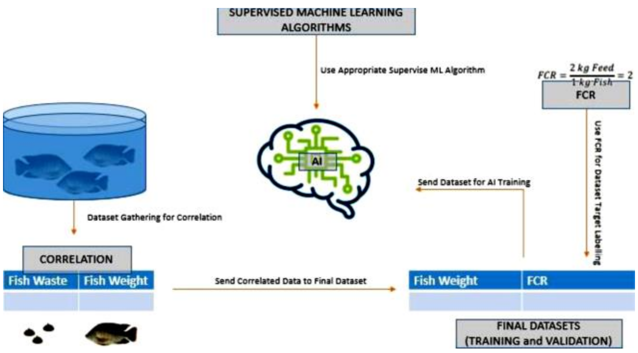

Fig. 3 Dataset Gathering and AI Training and Validation Block Diagram

Figure 3 shows the block diagram for the extraction of biophysical variables of the RAS to be used in the development of the AI model likewise the training and validation of the developed AI model.

To get data inputs for the machine learning to predict the tilapia right amount of feeds, the researcher, daily monitors the water Total Dissolved Solid (TDS), temperature, and pH level to get the average values for each day. The researcher also collects and measures daily the fish waste and food waste trapped in the filtration tank. To ensure that the maximum fish waste was collected, the researcher also manually collected using a net in the fish tank.

Temperate and pH levels are two water parameters to determine the amount of ammonia in the water. The increase of feed waste in the water will result in an increase in the ammonia level. Moreover, the Water Temperature level affects the tilapia's feeding behavior and metabolism. If the temperature decreases from the optimal level (25 - 30 degrees Celsius) tilapia fish tend not to eat. [12][13].

For the training and testing of the AI model, this study considered multiple linear regression machine-learning algorithms. The researcher used this algorithm to predict the right amount of feeds in a day using the water temperature level, Total Stocking Capacity (TSC), and Average Body Weight (ABW) of tilapia correlation on the feeding of tilapia as variables.

In addition, to derive the ABW, the researcher used Total Stocking Capacity (TSC), Total Dissolved Solids (TDS), and Ammonia as variables.

The researcher used the Jupyter Notebook Python 3 for the development and training of the AI model with the 364 recorded data that was collected in 3 months. After which the developed AI model undergoes cross-validation using the provided feature of sklearn in Python 3 through the use of ten thousand (10000) of test data.

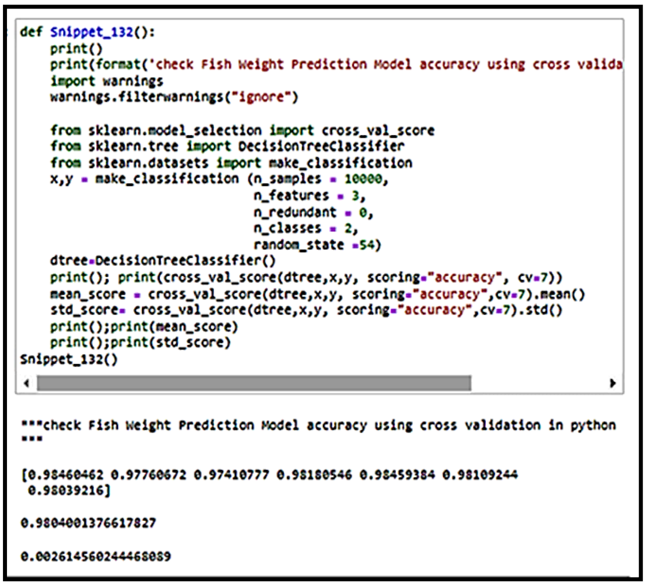

Fig. 4 Cross-validation of a fish Weight Prediction model using Multiple Linear Regression in Python

Figure 4 shows the cross-validation of the fish weight prediction model using multiple linear regression in Python.

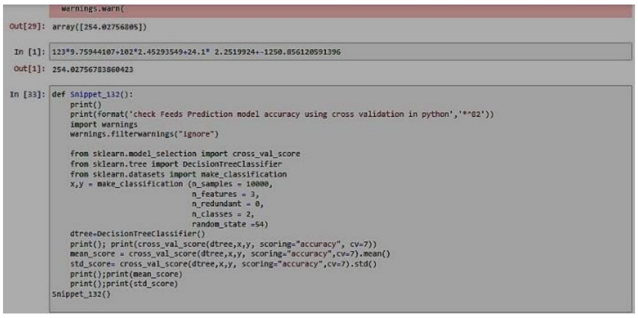

Fig. 5 Cross-Validation of AI Feeds Prediction using Multiple Linear Regression in Python

Figure 5 shows the cross-validation of the fish weight prediction model using multiple linear regression in Python. After the cross-validation, the AI model was extracted and deployed in the Arduino Uno for the actual testing and validation for at least 7 days.

The implementation of this project will be evaluated using the Feed- Conversion- Ratio to measure the efficiency with which the bodies of tilapia convert aquatic animal feed into the desired output.

$$FCR = \text{Ammount of feeds consumed (kgs)/Wet weight gain of fish (kgs)} \quad (3)$$

During the experiment period the researcher used 150 pcs of tilapia as the Total Stocking Capacity (TSC). The Tilapia Average Body Weight (ABW) started from 72 grams up to 251 grams which then reached a Total Wet weight gain of fish (grams) = 30,622.

3. Results And Discussion

In this study, the researcher was able to build a Recirculating Aquaculture System using low-cost and locally available materials such as 1m x 1.15m x 1.2m 1000 Liters IBC water storage tank, and three more water containers for the detection tank, filtration tank, and solution tank. These four tanks were connected using PBC pipes. The setup is considered a super-intensive culture system for tilapia since the fish were solely dependent on the feed provided and water is closely monitored and maintained. The Water used in the experiment was from deep-well and through the water recirculating feature, it can save water to a considerable amount. The water from the deep well was considered good for the survival and growth of the tilapia as presented in the water quality parameters reading. The readings were all in the allowable range and good for the growth of tilapia.

Table 2. Initial Water Parameter Reading of deep-well water

Water Parameter	Readings
pH level	8.6
Dissolved Oxygen	7.94 ppm
TDS Total Dissolved Solids	283 ppm
Temperature	25 degrees Celsius
Ammonia	0.2 ppm

Table 2 shows the initial water parameter reading of water coming from a deep well. This means that the water coming from deep-well is a desirable water quality for the growth of Nile tilapia based on the gathered water index suitable to the survival and growth of tilapia.

Table 3. Average Water Parameter Index Reading Comparison

Water Parameter	Reading when Recirculating is OFF at least 12 hours	Reading when recirculating is ON at least 1 hour	Reading continuous recirculating during daytime
pH level	5.67	7.79	7.43
Dissolved Oxygen	3 ppm	6 ppm	7 ppm
(TDS) Total	851 ppm	483 ppm	383 ppm Dissolved Solid
Temperature	29 ºC	27 ºC	25 ºC
Ammonia	2 ppm	0.2 ppm	0.01 ppm

Table 3 shows the water parameter index reading in different scenarios. This means that the recirculating system of the project maintains the water quality parameters to desirable levels for the survivability and growth of the Nile Tilapia. The mechanical and biological filtration included in the recirculated aquaculture system limits the amount of Ammonia, pH level, and TDS keeping the water quality at a desirable range for tilapia growth. It also contributes to maintaining a water temperature of 25 to 30 ºC which is good for the optimal growth of tilapia.

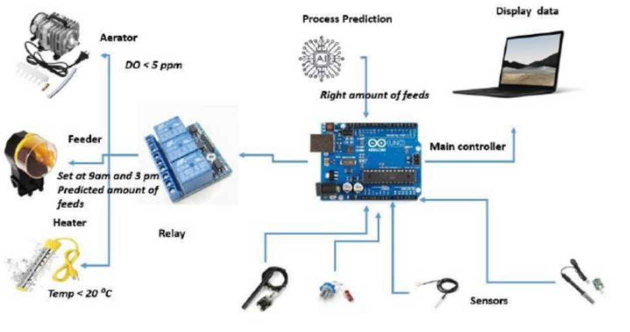

Fig. 6. Functional Block Diagram of the Intelligent RAS

Figure 6 shows the functional block diagram of how the intelligent RAS works. The intelligent feature of the system starts from the detection of the water quality parameter index by the different sensors namely the temperature, pH, TDS, and dissolved oxygen. Ammonia is being monitored mathematically using the temperature and pH level. Reading from the sensors will then be sent to the Arduino UNO where the main program is being stored. The reading will be processed and it will be displayed in the graphical user interface of the system on a laptop or PC and provided a proper notification message. The sensor readings were also used by the AI model to make the prediction. For cases where there is a water quality parameter index reading beyond the normal range of water quality, the main circuit which is the Arduino will send a signal to the relay to take necessary action to gain back the normal range of water quality suited for the survival and growth of tilapia. The aerator device will automatically switch ON when the dissolved oxygen reading is below 0.02 ppm, open the heater device when the water temperature drops to less than 20 ºC, and simultaneously provide a warning notification through the system interface for the fish farmer's information.

The 150 pieces of grow-out tilapia with an average of 72 grams in weight were the subject of the experimentation. The BFAR feeding schedule and feeding rate were observed during the experimentation period.

Table 4. Extracted Biophysical variables of the experiment.

Tilapia Average body weight (grams)	Amount of feeds.day (grams)	Average Food waste (grams)	Average Waste (Grams)	Average TDS Level	Average Ammonia Level
72	400	134	387	742	3
85.5	500	102	443	732	2
102	450	92	423	718	1
127	500	32	456	698	1
162	450	75	490	705	1
205	600	89	581	714	1
253	700	106	587	734	2

Table 4 shows the total amount of feeds given per day based on tilapia's average body weight. The feeding schedule adopted the twice-a-day scheme specifically at nine in the morning and three in the afternoon. The amount of feeds given per day in this table was derived using the formula on Daily Feed Rate (DFR) from BFAR:

*DFR=ABW*Stocking Density*feeding rate*

Furthermore, Table 4 shows the extracted biophysical variables such as the average food waste, average waste, average TDS reading, and average level of ammonia reading. This means that the increase in food waste resulted in a higher level of TDS and Ammonia in the water. The average Body Weight of tilapia can be directly associated with the amount of waste produced. As the weight of tilapia gets heavier, it produces more waste.

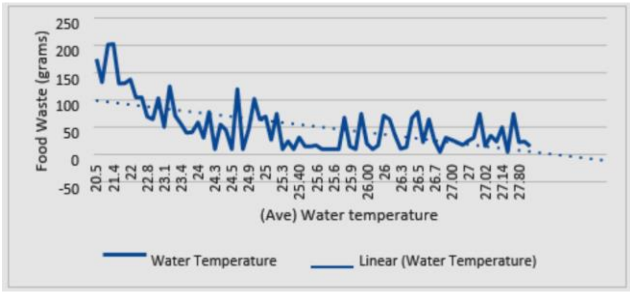

Fig. 6. Relationship of Food waste and Water Temperature

Figure 6 shows the relationship between water temperatures with food waste. This means that when the temperature is low, there is more food waste. This means that tilapia tends not to eat when the temperature is low. This was backed up by the fish farmer's practice of not feeding tilapia just after the rain or during the rainy days or cold season.

Table 5. Comparison of Predicted Amount of Feeds

Tilapia Average Body Weight (grams)	Amount of Feeds using BFAR formula (grams)	Actual amount given during experimentation (grams)	Amoun of feeds Predicted (grams)
72	432	400	408
85.5	384	350	360.87
102	257	278.57	265.53
127	310	297	308.53
162	395	407	396
205	500	450	499.97
253	617	600	612.93

Table 5 shows the comparison of the predicted amount of feeds to the actual given amount during experimentation and the amount of feeds derived using the BFAR formula. The figure presented in the table is the average feed per day derived based on the weight of tilapia. During the experimentation, there were dead tilapia. The initial 150 pieces became 122 pieces during the harvest time. The said dead was also considered in the computation of the amount of feeds. In the prediction model amount of feeds considered the temperature thus, it adjusts the amount when the temperature is low.

Table 6. Comparison of the Food-Conversion-Ratio

Amount of Feeds using BFAR formula (grams)	Actual amount given during experimentation (grams)	Amount of feeds Predicted (grams)	Accuracy
35,333	32,850	35,324.99998	99.98%

Table 6 shows the total amount of feeds given during the experimentation derived using the BFAR formula specified in equation 3, the prediction model, and the actual feeds given during the entire experimentation period. The daily feed or actual feed intake of fish in the tank was derived by the researcher by calculating the difference between the amount fed and the amount of waste feed collected (corrected for leaching losses). The predicted amount of feed is 99.98% compared to the BFAR formula and 93% compared to the amount of feeds given during the experimentation period.

The AI model for the prediction of feeds and prediction of ABW were also cross-validated as shown in Figure 9-10 in methodology where both get 98% linearity. This verified the accuracy of the prediction. The system was evaluated using the Feed-Conversion Ratio and its acceptability. Table 11 in methodology shows a comparison of the derived Feed-Conversion-Ratio or FCR. The result showed the feed prediction model is accurate as it has an FCR of 1.15 which according to BFAR a better fish feed. FCR is a formula used to compare and evaluate the efficiency with which the bodies of tilapia convert aquatic animal feed into the desired output.

4. Summary And Conclusion

In conclusion, this study represents a substantial advance in aquaculture, particularly with regard to the production of Oreochromis niloticus. The study has shown the potential to revolutionize the effectiveness, sustainability, and commercial viability of tilapia aquaculture by integrating an Intelligent Recirculating Aquaculture System (IRAS) with a Feed-Conversion-Ratio (FCR)-based Machine Learning (ML) method.

Feed Efficiency is improved: The incorporation of machine learning algorithms into the aquaculture environment allows for precise and real-time adjustment of feeding schedules and quantities based on FCR data. This results in significant feed waste reduction, a vital part of sustainable aquaculture, as well as significant cost savings for producers.

Improved Growth and Performance: The results show that the FCR-based ML technique improves Oreochromis niloticus growth rates and overall performance. The adaptive feeding method guarantees that fish get enough nourishment, resulting in healthier and more robust populations.

Economic viability: Feed cost reductions and improved growth rates contribute to aquaculture businesses' economic viability. Sustainable techniques that limit resource waste are not only good for the environment, but also good for business.

Sustainability in the Environment: The Intelligent Recirculating Aquaculture System reduces the environmental impact of traditional aquaculture systems. It decreases water pollution and the total ecological footprint of fish aquaculture by maximizing resource consumption.

Adaptation: The ML-driven system demonstrated adaptation to changing environmental circumstances, offering resilience in the face of unanticipated hurdles in aquaculture output.

In summary, findings in this study show that the FCR-based Machine Learning technique, when used in the context of an Intelligent Recirculating Aquaculture System, has the potential to improve the productivity and sustainability of Oreochromis niloticus aquaculture. Beyond this single species, the ideas revealed in this study hold promise for the larger aquaculture industry, providing a route toward more ethical and efficient aqua animal production that matches global food security and environmental preservation aims. As aquaculture continues to play an important part in supplying the world's protein demands, the new solutions presented here mark an important step forward in the industry's pursuit of a more sustainable and productive future.

5. Implications And Recommendations

5.1. Implications

In a worldwide context, the development of the aforementioned project can aid in the improvement and innovation of fish farming by allowing fish farmers to site their farms close to the populous and markets, allowing them to regulate year-round production and avoid weather extremes. Furthermore, the use of Artificial Intelligence would improve its sustainability and profitability, as well as provide fish farmers with convenience and comfort in administering their ponds or farms.

In an economic context, the development of a recirculated aquaculture system in fish farming helps promote a healthy environment for aquaculture products, which promotes fast growth, which can boost aquaculture production by providing fish vendors or businesses with a means to mitigate fish kills during transport and/or stocking, thereby providing consumers with fresher and healthier tilapia fish.

In the context of the environment, the development of this study enables aquaculture to take the technological turn required for the growth of this area with an eye toward environmental sustainability.

The implementation of research work could lead to the following:

Enhanced Aquaculture Efficiency: The integration of a supervised feed-conversion-ratio-based machine learning approach into the recirculating aquaculture system (RAS) for Oreochromis niloticus holds significant promise for improving overall efficiency. By continuously learning and optimizing the feeding process, the system can potentially reduce the wastage of feed, minimize environmental impact, and achieve higher fish growth rates.

Sustainable Aquaculture Practices: Sustainability is a crucial concern in modern aquaculture. This research highlights the importance of implementing intelligent systems in aquaculture to reduce the reliance on external inputs and decrease the overall ecological footprint. Such sustainable practices can help to preserve aquatic ecosystems and foster long-term viability for the aquaculture industry.

Application of Machine Learning in Aquaculture: The successful application of a supervised machine learning approach in the aquaculture system of Oreochromis niloticus opens doors for further research and application of artificial intelligence in other aquaculture settings. Researchers and industry professionals can explore the potential of machine learning for optimizing other processes, such as disease detection, water quality management, and species-specific husbandry practices.

Economic Viability: As aquaculture continues to play a crucial role in global seafood production, finding ways to reduce operational costs and increase productivity is essential. The incorporation of intelligent systems can lead to better resource management, reduced labor costs, and higher yields, ultimately contributing to the economic viability of the aquaculture industry.

5.2. Recommendations

Further Validation and Testing: While the initial results of this research are promising, further validation and testing of the intelligent recirculating aquaculture system are necessary. Conducting experiments in real-world conditions with larger sample sizes and varying environmental factors would provide more robust data to support the efficiency and effectiveness of the system.

Consideration of Different Fish Species: The focus of this research is on Oreochromis niloticus, but the approach should be evaluated for its applicability to other fish species commonly raised in aquaculture. Different fish species may have unique feeding behaviors and responses to environmental conditions, so adaptability should be thoroughly investigated.

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Conflicts of interest

The authors declare no conflicts of interest.

References

[1] V. Vishwakarma, A. Gurav, H. Patel, and S. Sahasrabudhe, Acqua culture monitoring system. 2018.

[2] J. A. V. Magsumbol, V. J. Almero, M. Rosales, A. A. Bandala, and E. P. Dadios, "A Fuzzy Logic Approach for Fish Growth Assessment," 2019 IEEE 11th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2019, pp. 9–12, 2019, doi: 10.1109/HNICEM48295.2019.9072756.

[3] Zhao, S., Zhang, S., Liu, J., Wang, H., Zhu, J., Li, D., & Zhao, R. (2021a). Application of machine learning in intelligent fish aquaculture: A review. Aquaculture, 540(March), 736724. https://doi.org/10.1016/j.aquaculture.2021.736724

[4] S. Mcginty and J. E. Rakocy, "Cage Culture Of Tilapia," Water, no. 281, pp. 1–13, 2021.

[5] O'Neill, E. A., Stejskal, V., Clifford, E., & Rowan, N. J. (2020). Novel use of peatlands as future locations for the sustainable intensification of freshwater aquaculture production – A case study from the Republic of Ireland. Science of the Total Environment, 706, 136044. https://doi.org/10.1016/j.scitotenv.2019.136044

[6] Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., & Zhou, C. (2021). Deep learning for smart fish farming: applications, opportunities and challenges. Reviews in Aquaculture, 13(1), 66–90. https://doi.org/10.1111/raq.12464

[7] Jie, C., Yingying, S., Junhui, W., Yusheng, W., Huiping, S., & Kaiyan, L. (2019). Intelligent Control and Management System for Recirculating Aquaculture. 2019 IEEE 2nd International Conference on Electronics and Communication Engineering, ICECE 2019, 438–443. https://doi.org/10.1109/ICECE48499.2019.9058567

[8] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors (Switzerland), 18(8), 1–29. https://doi.org/10.3390/s18082674

[9] Shen, S., Jiang, C., & Zhu, D. (2010). Modeling and simulation of milkfish farming and coral growth in Bolinao. 2010 International Conference on Computational Intelligence and Software Engineering, CiSE 2010. https://doi.org/10.1109/CISE.2010.5677121

[10] Africa, A. D. M., Aguilar, J. C. C. A., Lim, C. M. S., Pacheco, P. A. A., & Rodrin, S. E. C. (2017). Automated aquaculture system that regulates Ph, temperature and ammonia. HNICEM 2017 - 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management, 2018-Janua, 1–6. https://doi.org/10.1109/HNICEM.2017.8269494

[11] Nicolas-Mindoro, J. (2020). Fuzz-Fish-v2-IJATCSE. International Journal of Advanced Trends in Computer Science and Engineering.

[12] V. Vishwakarma, A. Gurav, H. Patel, and S. Sahasrabudhe, Acqua culture monitoring system. 2018.

[13] Ebeling, J. M., & Timmons, M. B. (2012). Recirculating Aquaculture Systems. Aquaculture Production Systems, 245–277. https://doi.org/10.1002/9781118250105.ch11

[14] X. Peng, L. Chen, Y. Yu, and D. Wang, "PCA-GRNN-GA Based PH Value Prediction Model Applied in Penaeus

Orientalis Culture," Proc. - 2016 Int. Conf. Digit. Home, ICDH 2016, pp. 227–232, 2017, doi: 10.1109/ICDH.2016.054.

[15] T. J. Akaahan, "Evaluation of Water Quality Suitability in River Benue at Makurdi for Aquaculture Production in Benue State, Nigeria," Int. Sci. Res. J., vol. 1, no. 06, pp. 66–73, 2015, doi: 10.18483/irjsci.64.

[16] D. M. Africa, J. C. C. A. Aguilar, C. M. S. Lim, P. A. A. Pacheco, and S. E. C. Rodrin, "Automated aquaculture system that regulates Ph, temperature and ammonia," HNICEM 2017 - 9th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag., vol. 2018-Janua, pp. 1–6, 2017, doi: 10.1109/HNICEM.2017.8269494.

[17] S. Shen, C. Jiang, and D. Zhu, "Modeling and simulation of milkfish farming and coral growth in Bolinao," 2010 Int. Conf. Comput. Intell. Softw. Eng. CiSE 2010, 2010, doi: 10.1109/CISE.2010.5677121.

[18] W. Shan, S. Cai, and C. Liu, "A new comprehensive evaluation method for water quality: Improved fuzzy support vector machine," Water (Switzerland), vol. 10, no. 10, 2018, doi: 10.3390/w10101303.

[19] X. Xia, Z. Yang, G. H. Huang, and I. Maqsood, "Integrated Evaluation of Water Quality and Quantity of the Yellow River," Water Int., vol. 29, no. 4, pp. 423–431, Dec. 2004, doi: 10.1080/02508060408691804.

[20] L. L. Loyola, L.G., Lacatan, "Survivability of Aqua Marine Products in Fish Ponds through Water Quality Evaluation Using Machine Learning Algorithm," Test Eng. Manag., vol. 82, no. February, pp. 3954–3960, 2020, [Online]. Available: https://www.academia.edu/42475808/Survivability_of_Aqua_Marine_Products_in_Fish_Ponds_through_Water_Quality_Evaluation_Using_Machine_Learning_Algorithm?from=cover_page.

[21] C. Feng, J. Yuan, Y. Sun, and J. You, "Design of Water Quality Monitoring System," Proc. - 2020 Int. Conf. Artif. Intell. Comput. Eng. ICAICE 2020, pp. 264–267, 2020, doi: 10.1109/ICAICE51518.2020.00057.

[22] R. Islam et al., "Assessment of pH and Total Dissolved Substances (TDS) in the Commercially Available Bottled Drinking Water," vol. 6, no. 5, pp. 35–40, 2017, doi: 10.9790/1959-0605093540.

[23] M. Endler, J. P. Briot, F. Silva E Silva, V. P. De Almeida, and E. H. Haeusler, "Towards stream-based reasoning and machine learning for IoT applications," 2017 Intell. Syst. Conf. IntelliSys 2017, vol. 2018-Janua, no. September, pp. 202–209, 2018, doi: 10.1109/IntelliSys.2017.8324292.

[24] R. Medar, V. S. Rajpurohit, and B. Rashmi, "Impact of Training and Testing Data Splits on Accuracy of Time Series Forecasting in Machine Learning," 2017 Int. Conf. Comput. Commun. Control Autom. ICCUBEA 2017, no. April 2020, pp. 1–6, 2018, doi: 10.1109/ICCUBEA.2017.8463779.

[25] N. Li, Z. Fu, W. Cai, and X. Zhang, "Using Support Vector Machines to Predict the Variation of Organic Pollutants in Pond Water," IEEE, 2007. https://www.infona.pl/resource/bwmeta1.element.ieee-art-000004304482/tab/summary (accessed Jan. 15, 2022).