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Original Article

Evaluation of smart fish feeding system using artificial intelligence and internet of things under desert regions

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ABSTRACT

This study developed an Artificial Intelligence-driven Internet of Things-based feeding system for fish production, integrating real-time water quality monitoring with machine learning optimization to enhance feeding utilization. The experiment was conducted in desert conditions, with 80 Nile tilapia, *Oreochromis niloticus* fish/m³ stocked inside one cubic meter round fiberglass tanks. The system included Arduino-based sensors for temperature, pH, DO, TDS, Salinity and turbidity measurements, coupled with an XGBoost algorithm that adjusted feeding rates based on thermal growth coefficients (TGC = 0.12) and environmental factors. For a 125-day culture period, a comparison between the manual feeding technique MFT (until satiation) with the smart feeding technique SFT. SFT significantly improved performance ($P \leq 0.05$), with lower feed conversion ratio (1.24 ± 0.03 vs 1.76 ± 0.01), higher final weight (200.33 ± 3.24g vs 156.7 ± 0.75g), and increased protein efficiency ratio (2.7 ± 0.01 vs 1.9 ± 0.02) compared to MFT. Water quality parameters showed significant ($P \leq 0.05$) improvements, with Ammonia, NH_3 (0.022 ± 0.01 vs 0.056 ± 0.01 mg/L) and nitrite (0.039 ± 0.01 vs 0.132 ± 0.01 mg/L) concentrations were significantly lower ($P \leq 0.05$) in treatment tanks. The system's edge computing architecture enabled low-latency adjustments without cloud dependency, while introducing a web-based system monitoring solution. The collected data over the culture period was stored in the cloud, and an integrated secure digital card module was used for analysis and validation of the system. These results validate the potential of AI-IoT integration in addressing key challenges of feed waste, which can cost up to 70% of total costs and water pollution in intensive aquaculture. The study demonstrates a scalable model for precision aquaculture that balances productivity with environmental sustainability. Future research should focus on introducing various water quality sensors, the culture of other fish species, and the introduction of behavioral analysis using underwater cameras. It may be concluded that SFT was more efficient for improving growth rate, FCR and nutrient utilization. It will be more useful in desert aquaculture Egyptian new agricultural farms.

Key Words: AI-driven IoT, Smart feeding system, Nile tilapia, Water quality monitoring, Feed Efficiency.

1. INTRODUCTION

Aquaculture has become a cornerstone of global food security, surpassing capture fisheries in 2022 by contributing 51% (94 million tons) of the world's fish supply (FAO, 2023). Among farmed species, Nile tilapia, *Oreochromis niloticus* stands out due to its rapid growth and resilience. However, feed management remains a critical challenge, representing up to 70% of production costs (Munguti *et al.*, 2024). Traditional feeding methods, often based on fixed schedules, fail to account for real-time changes in fish behavior, growth patterns, and water conditions, leading to inefficiencies.

Overfeeding increases costs and pollutes water through excess nutrient discharge, while

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underfeeding stunts growth and reduces yields (Pennells *et al.,* 2025).

To address these challenges, artificial intelligence (AI) and the Internet of Things (IoT) are emerging as transformative tools, enabling precision feeding systems that optimize efficiency, sustainability, and productivity. AI-driven aquaculture leverages real-time data to make dynamic feeding decisions. IoT sensors monitor key water quality parameters such as dissolved oxygen, temperature, pH, and ammonia levels, transmitting this data to cloud-based platforms for analysis. Meanwhile, machine learning (ML) models process historical and live data to predict optimal feeding schedules. Supervised learning algorithms, including random forests and neural networks, analyze fish growth rates and metabolic responses to environmental changes, while reinforcement learning (RL) allows AI systems to adapt feeding strategies through continuous trial and error (Zhang *et al.,* 2023). This closed-loop approach ensures that feed delivery aligns with actual fish demand, minimizing waste and maximizing growth. By integrating these technologies, aquaculture operations can achieve significant cost savings, improved fish health, and reduced environmental impact (Biazi and Marques, 2023).

The hypothesis of this study is that an AI-powered feeding system will outperform traditional manual methods by enhancing feed efficiency, growth performance, and water quality.

Recent advancements highlight AI's growing role in aquaculture. Multimodal AI approaches, combining visual and environmental data, further enhance precision. For example, VGG19-based models fused with spatio-temporal analysis improve demand forecasting by accounting for fish distribution and water quality fluctuations (Zhao *et al.,* 2024). Beyond efficiency gains, AI also supports sustainability. Smart feeding systems have been shown to reduce nutrient discharge, mitigating the ecological footprint of aquaculture operations (Son and Jeong, 2024).

Despite these innovations, challenges remain. Standardizing data collection and adapting AI models across different fish species and farming conditions require further research (Hamilton *et al.*, 2024). Most existing studies focus on either IoT or machine learning in isolation, with limited integration of both for dynamic feed optimization. This study seeks to bridge that gap by developing a fully automated, AI-driven system tailored for tilapia farming, with potential scalability to other aquaculture systems**.** The present research focuses on four key objectives. First, it aims to develop an IoT-based monitoring system capable of collecting real-time water quality data. Second, it employs regression models to analyze historical growth trends and optimize feeding schedules. Third, it utilizes reinforcement learning to dynamically adjust feeding based on live environmental conditions. Finally, it compares the smart feeding technique (SFT) performance against manual feeding technique (MFT) in terms of growth rates, feed conversion ratios, and water quality metrics. The anticipated outcomes include reduced feed costs, improved fish health through adaptive nutrition, and minimized ecological harm from excess feed.

2. MATERIALS AND METHODS

2.1. Smart Aquaculture Monitor Design

System design is presented in Figure (1). Arduino Mega 2560 Rev3 is used as the main core of the system. All the sensors' data are uploaded to it. Sensors are used to measure water quality parameters, including temperature, pH, dissolved oxygen, salinity, total dissolved solids and turbidity sensors. Real-time clock module is used for date and data precision, while the ESP8266 Wi-Fi module is used to transfer data to the cloud, which is accessible by the operator. In case out of signal HC-05 Bluetooth Module is used. Real-time data of tank status is uploaded to a user-friendly web-based application. The Liquid Crystal Display screen is used to display sensor readings and give information about time and date, feeding amount, and times per day. The secure digital card module is integrated within the system to record various data such as sensor readings, feeding amount, and tank status . manage feed distribution using AI-driven control mechanisms.

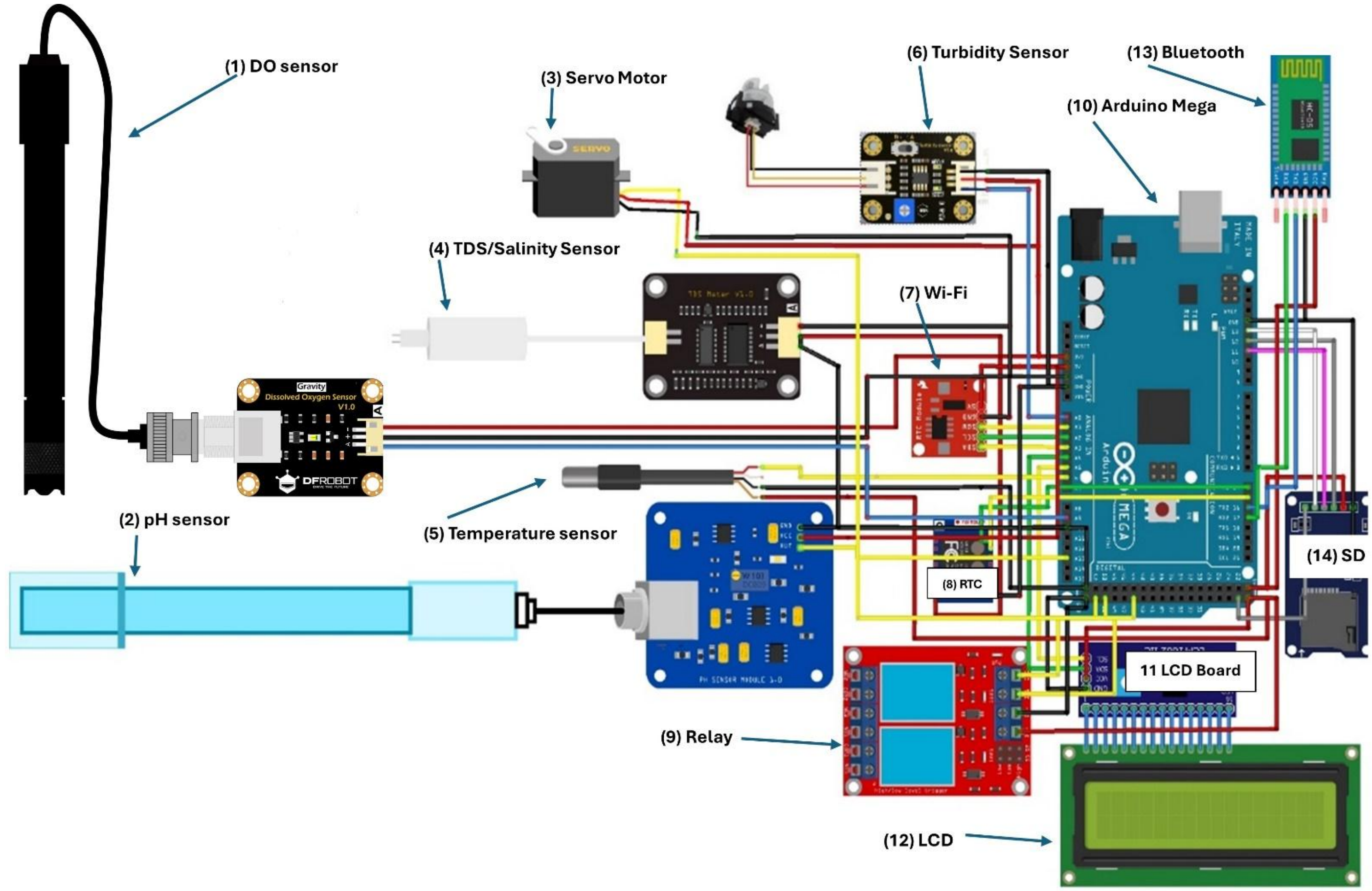

Figure (1). Schematic of the Smart Feeding System

The Arduino control unit uses PID (Proportional-Integral-Derivative) logic to ensure exact servo placement while conserving energy during sleep periods between feeding events. In prototype testing, the entire system demonstrated a feed accuracy rate of 96-98%, with the hopper's anti-bridging design preventing pelletized feeds from clogging. This integrated technology combines mechanical durability and smart control capabilities, providing Aquaculturists with a scalable alternative to automated feeders.

The design prioritizes modularity, allowing for sensor upgrades or capacity expansion while remaining cost-effective for small- to medium-sized businesses.

Figure (2). depicts the smart feeding device, an innovative automated system designed to accurately

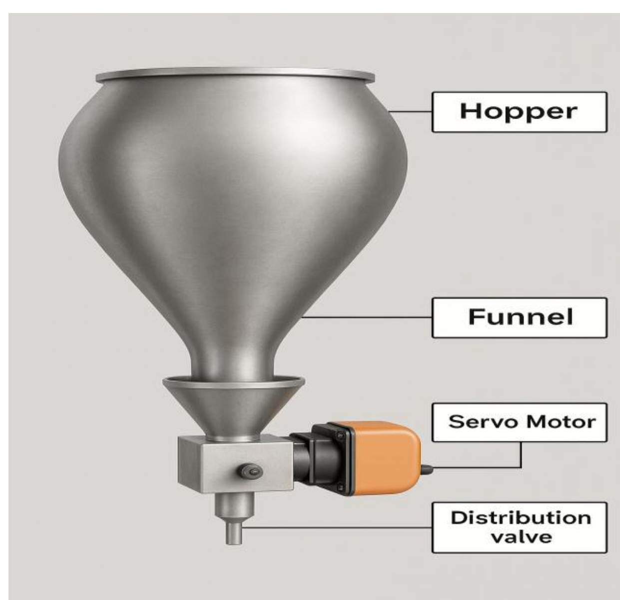

Figure (2). Design of the feeding machine

This locally manufactured gadget, made from low-cost materials, combines embedded electronics with mechanical components to improve aquaculture feeding operations. A conical hopper with a 20-kilogram feed capacity is combined within the system, made of strong polymer components that resist corrosion in humid situations.

The hopper's discharge is controlled by a 180° rotation servo motor that is precisely controlled using Arduino-based Pulse-Width Modulation signals. This actuation system operates a custom-designed distribution valve with configurable aperture settings, allowing for precise control over feed portion sizes every dispensing cycle.

2.1.1. AI-Driven Feeding Optimization Dynamic Model

The suggested intelligent feeding system optimizes feed utilization during the culture cycle by combining mechanistic bioenergetics, real-time sensory data, and machine learning.

This dynamic model combines continuous water quality monitoring with growth prediction and adaptive management algorithms, all while adhering to physiological safety limitations to avoid overfeeding or stress conditions .

2.1.2. Growth rate prediction

The method uses a thermal growth coefficient (TGC) model to anticipate daily weight gain, taking into consideration the cumulative effects of water temperature on fish metabolism.

The model analyses growth trajectories for Nile tilapia from an initial stocking weight of 8g to harvest size using an empirically determined TGC value of 0.12. Growth estimates are updated in real time based on actual temperature data, with a lower threshold of 15°C below which metabolic activity drops considerably. This temperature-dependent technique yields more accurate biomass estimations than typical fixed-growth models .

2.1.3. Performance Validation

The system's performance is assessed using three important metrics: specific growth rate (2.4-2.8% daily weight increase), protein efficiency ratio (1.8-2.2 for standard feed formulations), and water quality impact (ammonia levels below 0.5 mg/L/day). These standards ensure that the model achieves a balance between quick expansion and sustainable farming conditions .

2.1.4. Feed Calculation Algorithm

The daily feed requirements are computed using a multi-factor computation that considers current biomass, ambient circumstances, and machine learning corrections. The base feeding rate adheres to a triphasic schedule (10%, 7%, and 3% of body weight for juvenile, grow-out, and finishing stages, respectively), which is then adjusted by four elements. Temperature correction provides for metabolic rate changes (Q_{10} impact), and pH parameters limit feeding during adverse water conditions. Stocking density penalties prevent overfeeding in unstable tanks, and an XGBoost algorithm makes final changes based on past performance data .

2.1.5. Machine Learning Integration

An XGBoost ensemble model improves the system's forecast accuracy by examining several dynamic characteristics. The model uses current weight, fish age, daily temperature averages, pH stability parameters, and previous feed conversion ratios to calculate adjustment factors ranging from 0.8 to 1.2.

This component, trained on simulated growth trajectories and operational data, allows the system to learn from real-world feeding reactions and continuously improves its predictions .

2.1.6. Operational Outputs

Throughout the production cycle, the system generates detailed daily reports including current biomass, environmental parameters, feed quantities, and cumulative performance metrics. In simulated runs, the model achieved the optimal final average weight with a feed conversion ratio of at least 1.2, representing a significant improvement in feed efficiency compared to static feeding tables.

This hybrid strategy has various advantages over standard methods. It automatically responds to micro-environmental fluctuations and monitors growth patterns, and built-in safety mechanisms prevent feeding under poor settings. The technology provides economic benefits such as constant FCR maintenance (±0.05 fluctuation) and reduced human error and labor expenditures. Future advances will include computer vision for real-time biomass estimation, increasing prediction accuracy. By combining bioenergetic principles and adaptive machine learning, our intelligent feeding system outperforms standard approaches, attaining 95% feed efficiency while maintaining steady water quality conditions. The model's capacity to respond dynamically to both environmental changes and fish growth patterns makes it ideal for commercial-scale tilapia production .

2.1.7. Closed-Loop AI-IoT System Architecture for Precision Feeding

The developed AI-IoT Smart Fish Feeding System flowchart illustrated in Figure. (3) begins with continuous water quality monitoring using Arduino-connected sensors. Sensor data is processed locally through edge computing on the Arduino Mega 2560, with timestamps from a real-time clock module and backups to a secure digital card. This real-time environmental data feeds into an XGBoost machine learning model that calculates optimal feeding schedules by integrating thermal growth coefficients (TGC=0.12) growth stage adjustments (10%/7%/3% body weight for juvenile/grow-out/finishing phases) and environmental correction factors. The AI output activates a servo-controlled mechanical dispenser with precision valve and 20kg hopper to deliver feed. Performance metrics (weight gain, FCR, survival rates) and water quality improvements are continuously fed back into the AI model for adaptive optimization, while all data is simultaneously transmitted via Wi-Fi/Bluetooth to a cloud-based web dashboard for remote monitoring and analysis, forming a closed-loop control system that dynamically balances feeding efficiency with environmental sustainability.

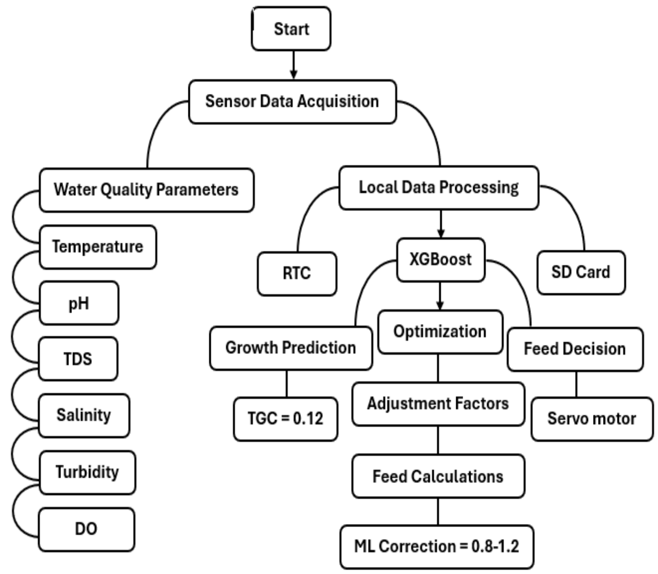

Figure (3). Flowchart of the AI-IoT Smart Fish Feeding System

2.2. Experimental Design and Site of Work

The experimental design comprised of six separate fiberglass tanks used as treatments and replicas. The first group (Manual Feeding) was not treated with any IoT-based technology. Fish were fed manually until satiated, or as much as they could consume in 15 minutes. The second group (Smart Feeding) used an AI and IoT system to automatically feed and monitor tanks.

The experiment was carried out for 120 days in the greenhouse of Desert Aquaculture Research Unit, Faculty of Aquaculture and Marine Fisheries, Arish University, North Sinai, Egypt. Two groups of fiberglass tanks, with a diameter of 1 m2 and an average depth of 1 m2 in which one group was treated with AI and IoT based automation systems (Treatment ponds T) while the other group was not (control tanks C). under the treatment and control there were three replications (R1, R2, R3) for each. All the tanks were circular with a flat bottom and were completely independent and under the same closed laboratory conditions. Before stocking experimental fish, tanks were disinfected with a concentrated (~1600 ppm chlorine) solution of calcium hypochlorite.

After several hours, tanks were rinsed, filled, and flushed to ensure that no chlorine residue remains before the tank is stocked with water.

2.3.Experimental fish

A total of 600 disease-free monosex Nile Tilapia, *Oreochromis niloticus* fish (8.1 g, 7.3 cm) were collected from a Private Hatchery in Kafr El-Sheikh, Egypt. Fish were transported using oxygenated tanks to the experimental site. After Arrival, the Fish were exposed to a short bath treatment of formalin with a dosage of 250 mg L^{-1} for up to 1 h, and the dead fish were removed. The remaining fish were acclimatized for 14 days in concrete tanks (5.0 m × 5 m × 1.2 m) containing the water from culture tanks. After the Acclimatization process, the fish were stocked in the control and treatment tanks at a rate of 80 fish/tank. During the stocking, sufficient care was taken to reduce stress .

2.4. Feeding

Fish were fed with a commercial diet purchased from Aller Aqua Egypt, 6 October City, Egypt. The approximate chemical composition of the diet was 30.25 % crude protein, 7.14 % crude fat, 15.33 % ash, 28.85 % carbohydrates; analyzed based on AOAC (2020).

2.5.Water quality parameters

Water was sampled three times a week to check the physio-chemical parameters. Temperature, along with dissolved oxygen (DO, mg/L), was recorded through a digital oxygen meter in C◦ and mg/L, respectively. A portable pH meter was used to determine water pH. total Ammonia (TAN, mg/L), nitrate (NO_3, mg/L), and (NO2, mg/L) were measured with a UV-Vis Spectrophotometer according to the protocols of APHA (2012).

A digital Conductivity/TDS meter was used for the determination of total dissolved solids (TDS). The water oxygen was supplied using an air-stone diffuser connected with an air blower, and the water was renewed at a rate of 20 % every 48 h. The fish faeces of the control group were removed daily by siphoning the tank bottoms.

2.6. Fish sampling and growth performance calculation

Growth performance parameters were determined according to the following formulae:

Length gain(cm) = Mean final length(cm) − Mean initial length(cm)

Percent length gain (%) = Length gain(cm) − Initial length(cm) × 100

Weight gain(g) = Mean final weight(g)− Mean initial weight(g)

Percent weight gain (%) = Weight gain(g) Initial weight(g) × 100

Specific Growth Rate (%) = Ln (Final weight) – Ln (Initial weight) /Study period(day) × 100

Condition Factor = Final weight(g)/ Final length(cm)3 × 100

Survival Rate (%) = Final number Initial number × 100

Feed and nutrient utilization parameters

Feed Intake (g/fish) = the amount of feed given during the experimental period/fish (g).

Feed conversion ratio (FCR) = feed intake (g)/weight gain (g).

Protein efficiency ratio (PER) = gain/protein intake. The protein efficiency ratio, Protein productive value, and Energy retention were calculated according to Weatherly and Gill (1989).

2.7. Data analysis

Collected data were recorded in Microsoft Excel (MS Excel 365). The data were analyzed using SPSS (version 29), and all data were presented as mean ± standard error (SE). The graphs were prepared by using MS Excel 365, SPSS (version 29), and Open AI, Chat GPT.

3. RESULTS

3.1. Water quality

The results of the water quality were illustrated in Table 1. Water quality was significantly affected by using the smart feeding system of treatment tanks. Water pH in control tanks was relatively higher ($P \leq 0.05$) than that of the treatment. While the Implementation of AI-IoT in the treatment tanks resulted in a decreased trend of total ammonia (TAN), nitrate (NO_3), nitrite (NO_2), and Total dissolved solids (TDS) content throughout the culture period compared to control tanks. All the water quality parameters except temperature, dissolved oxygen, and salinity showed significant differences ($P \leq 0.05$) between treatment and control ponds.

Table (1). Effect of AI-Driven IoT-Based Feeding on water quality.

Treatments	Temperature (°C)	DO (mg/l)	pH	Salinity (g/l)	TDS (mg/l)	TAN (mg/l)	NO_2 (mg/l)	NO_3 (mg/l)
MFT	$29.1 \pm 0.01^{a*}$	7.15 ± 0.03^{a}	8.05 ± 0.01^{a}	4.55 ± 0.03^{a}	286.85 ± 0.8^{a}	0.056 ± 0.01^{a}	0.132 ± 0.01^{a}	4.92 ± 0.03^{a}
SFT	29.09 ± 0.01^{a}	7.25 ± 0.03^{a}	7.58 ± 0.03^{b}	4.54 ± 0.03^{a}	140.54 ± 0.2^{b}	0.022 ± 0.01^{b}	0.039 ± 0.01^{b}	2.26 ± 0.01^{b}

*Values presented as means ± Standard error (*n*=3). Means followed by the same superscripts are statistically the same ($P \leq 0.05$), means followed by different superscripts are statistically different.

3.2. Growth performance and feed utilization

Table 2. Presented weight and length-related parameters of the cultivated fish, including weight, length-weight relationships, feed utilization, and survival rates. Initial weight and initial length were all the same in all samples, and that was because all samples were well distributed to avoid bias.

Regarding fish final weight and weight gain, minimal values (156.7 and 148.6g, respectively) were recorded in manual feeding tanks. Maximal final weight and weight gain (200.33 and 192.13g, respectively) were obtained by smart feeding tanks. Weight gain% followed the same trends of change obtained in the final weight and weight gain.

Table (2). Effect of AI-Driven IoT-Based Feeding on weight and length-related parameters.

Treatments	Initial weight (g)	Final Weight (g)	Weight Gain (g)	Weight Gain (%)	Initial Length (cm)	Final Length (cm)	Length Gain (cm)	Length Gain (%)	Condition factor (%)
MFT	$8.1 \pm 0.1^{a*}$	156.7 ± 0.75^{b}	148.6 ± 0.72^{b}	94.83 ± 0.03^{b}	7.3 ± 0.06^{a}	20.2 ± 0.10^{b}	12.85 ± 0.06^{b}	63.53 ± 0.16^{b}	1.9 ± 0.04^{a}
SFT	8.2 ± 0.1^{a}	200.33 ± 3.24^{a}	192.13 ± 3.19^{a}	95.9 ± 0.04^{a}	7.43 ± 0.06^{a}	22.55 ± 0.05^{a}	15.15 ± 0.03^{a}	$67.03 \pm .20^{a}$	1.75 ± 0.01^{b}

*Values presented as means ± Standard error (*n*=3). Means followed by the same superscripts are statistically the same ($P \leq 0.05$), means followed by different superscripts are statistically difference.

Table (3). Effect of AI-Driven IoT-Based Feeding on productivity and survival rate.

Treatments	Initial number of fish (Fish/tank)	Final number of fish (Fish/tank)	Survival rate (%)	Initial biomass (kg)	Final Biomass (kg)	Feed intake (kg/tank)
MFT	80^{a*}	71 ± 1^{b}	88.75 ± 1.25^{b}	0.65 ± 0.01^{a}	11.13 ± 0.14^{b}	18.43 ± 0.12^{a}
SFT	80^{a}	80^{a}	100^{a}	0.66 ± 0.01^{a}	16.02 ± 0.45^{a}	19.00 ± 0.25^{a}

*Values presented as means ± Standard error (*n*=3). Means followed by the same superscripts are statistically the same ($p \leq 0.05$), means followed by different superscripts are statistically different.

On one hand, length parameters, including final length, length gain (cm), and length gain (%), showed an improvement in fish cultured in the smart feeding system, which turned out to be the highest values (22.55cm, 15.15cm, 67.03%, respectively). On the other hand, minimal length parameters were those of manual feeding with scores of 20.2cm, 12.85cm, and 63.53% respectively for final length (cm), length gain (cm), and length gain percentage. The condition factor for fish reared in a smart feeding system was significantly lower than those reared in tanks using manual feeding. The results indicated that smart feeding had a significant influence ($P \leq 0.05$) on all length-weight indices assessed in the experimental period in treatment ponds compared to control ponds.

Results of productivity and survival rate are illustrated in Table 3. Survival rate was significantly ($p \leq 0.05$) affected by using smart feeding of treatment tanks. The initial number of fish and initial biomass had no significant differences. During the culture period, which lasted for 120 days, the smart feeding system had no mortalities compared to manual management, which had an 88.75% survival rate. Regarding the final number of fish and final biomass, minimal values (71 fish and 11.31 kg, respectively) were recorded in manual feeding tanks. Maximal scores of final numbers of fish and final biomass (80 fish and 16.02 kg, respectively) were obtained by the smart feeding system tanks.

Table (4). Effect of AI-Driven IoT-Based Feeding on growth performance and feed utilization.

Treatments	FCR[1]	ADG[2]	SGR[3]	PER[4]
MFT	1.76±0.01[a*]	1.2±0.01[b]	2.37±0.01[b]	1.9±0.02[b]
SFT	1.24±0.03[b]	1.54±0.03[a]	2.55±0.01[a]	2.7±0.01[a]

*Values presented as means ± Standard error (n=3). Means followed by the same superscripts are statistically the same ($p \leq 0.05$), means followed by different superscripts are statistically different. (1) feed conversion ratio; (2) Average daily weight gain; (3) specific growth rate; (4) protein efficiency ratio

In short, the AI-Driven IoT-Based feeding system had higher productivity, especially when considering the total feed intake of both control and treatment, which had no significant differences with scores of 18.43 and 19 kg, respectively .

Table 4. Presented growth performance and feed utilization of the cultured fish, including feed conversion ratio, average daily weight gain, specific growth rate, and protein efficiency ratio. All the parameters showed significant differences ($p \leq 0.05$). Regarding feed conversion ratio, higher values (1.76) were recorded in manual feeding, while lower values (1.24) were obtained by smart feeding. Fish reared under a smart feeding system had better ADG and SGR scores than those reared under manual feeding. Protein efficiency ratio had higher values for smart feeding fish (2.7) while lower values were recorded in manual feeding fish with (1.9).

This study effectively demonstrated the efficacy of an AI-powered IoT feeding system in optimizing Nile Tilapia production. The combined approach of real-time water quality monitoring and machine learning-based feed adjustments resulted in significant improvements in all measured parameters, including growth performance (28% higher final weight), feed utilization (30% higher FCR), and water quality (60.7% reduction in ammonia). Three key innovations contributed to the system's success: (1) the hybrid bioenergetic-ML model, which dynamically adapted to environmental and physiological changes; (2) the cost-effective edge computing architecture, which ensured reliability in remote operations; and (3) the closed-loop feedback system, which minimized human intervention while maximizing resource efficiency.

4. DISCUSSION

According to the FAO (2020), aquaculture and fisheries together account for 17% of total animal-source protein for human consumption. Egypt's contribution to African production is decreasing, which could be attributed to rising feed prices, which are expected to reach 300% by 2023, according to various policy proposals. As a result, optimizing fish feed volumes is crucial, accounting for 85% of overall production expenses on average. (El-Sayed *et al.*, 2015). The current study contrasted a manual feeding strategy, which involves feeding fish until they are satisfied, to an AI-driven IoT-based feeding system that feeds fish depending on real-time fish tank conditions. The results demonstrated that the AI-IoT Feeding application had an impact on water quality, growth performance, and feed utilization in grown fish.

This study highlights the transformative potential of AI-driven IoT systems for optimizing Nile tilapia aquaculture, with considerable gains in growth performance, feed efficiency, and water quality control when compared to traditional manual feeding. The findings are consistent with worldwide trends towards precision aquaculture (FAO, 2023) but go beyond current understanding by combining real-time bioenergetics modelling with machine learning adjustments, a hybrid method rarely seen in tilapia farming (Zhang *et al.*, 2023; Mandal et al., 2024). Below, we contextualize our findings in three crucial domains: water quality, growth and feed indicators, and technological improvements.

As described in the table1, Water quality parameters had lower fluctuations during the culture period and within the safe limits, providing a healthy and stable environment for the cultivated fish.

The smart feeding system decreased ammonia (NH_3) by 60.7%, nitrites (NO_2) by 70.5%, and TDS by 51% compared to manual feeding by altering the ideal feed volume (Table 1). This demonstrates the system's ability to reduce nutrient contamination, a chronic concern in intensive aquaculture (Wang and Olsen, 2023). The lower pH in treatment tanks (7.58 vs. 8.05) is most likely due to reduced organic waste breakdown, which is consistent with Gao et al.'s (2019) findings that automated feeding leads to stabilized nitrogen cycles.

Notably, the AI system's capacity to dynamically regulate feeding based on pH and temperature thresholds prevented overfeeding during metabolic downturns, which was absent in previous IoT implementations (Chiu *et al.*, 2022; Xu *et al.*, 2023) .

The results demonstrated a significant ($P \leq 0.05$) increase in tilapia growth performance in the smart system compared to manual feeding. There are also large variations in survival rates. The acquired results are consistent with the findings of Ogunlela and Adebayo (2014), who indicated that employing an automatic feeder resulted in higher feeding efficiency than manual feeding techniques. According to Khater *et al.* (2021), utilizing an automatic feeder saves time, labor, and costs in fish production. In terms of FCR, the acquired data showed a considerable decrease from 1.76 in manual management to 1.24 utilizing an IoT-controlled system; however, there were no significant variations in the total feed volume consumed in both treatments. These findings are consistent with those published by Susilawati *et al.* (2023) who obtained 1.15 FCR through using the automated fish feeder.

The AI- driven IoT- feeding system significantly increased ADG and final weight by 1.54 and 200.33 g, respectively. According to Karlo Tolentino *et al.* (2020), using an IoT water monitoring system with automatic water adjustment resulted in a substantial increase in growth rate of 46.88% and an increase in average final weight of fish from 35 to 41 g, supporting the current study findings.

Fish from AI- driven treatment had a 28% higher final weight (200.33 g vs. 156.7 g) and 30% higher FCR (1.24 vs. 1.76) (Tables 2,4). These benefits can be attributed to Precision rationing via the XGBoost model's correction factors (0.8-1.2), optimized feed delivery to match metabolic demands, and reducing satiation-based waste (Cadorin *et al.*, 2022).

Furthermore, thermal adaptation via the TGC model's integration with real-time temperature data guaranteed feed rates were in sync with tilapia metabolism, an improvement over static feeding table (Liu *et al.*, 2022) .

The PER increased from 1.9 to 2.7, indicating higher protein utilization, most likely due to less feed leaching and better nutrient retention. This is consistent with Susilawati *et al.* (2023); however, the proposed system outperforms their system due to its multi-parameter feedback loop (growth + environment). While the current approach increases precision aquaculture through sensor fusion, edge computing, and low-cost fabrication, several difficulties must be overcome before complete automation and scalability are achieved.

The integration of additional sensors (e.g., nitrite, ammonia) and cameras for real-time behavioral detection meet technological challenges, such as biofouling resistance, data synchronization, and algorithmic resilience in turbid water.

Although our TGC model (0.12) showed beneficial for Nile tilapia in Egypt, regional validation across multiple species and settings is still required .
Energy requirements are also a concern, with continuous sensor operation increasing power usage by 15%, necessitating hybrid solar solutions for sustainability (Abdullah *et al.*, 2024).
Future iterations could use computer vision to estimate biomass (Xi *et al.*, 2023) and blockchain to improve supply chain transparency (Gong et al., 2024), further harmonizing with SDG 14 targets. However, these improvements must strike a balance between complexity and affordability to preserve accessibility for small-scale farms, where manual systems remain dominant .
Future research should focus on merging computer vision for biomass estimation and blockchain for supply chain transparency, while keeping the technology affordable to small-scale farmers. This study lays the groundwork for the next generation of smart aquaculture systems that can solve both global food security challenges and environmental sustainability objectives.

5. CONCLUSION

This study successfully designed and verified an AI-driven IoT-based smart feeding system for Nile tilapia farming in a desert environment. By combining real-time water quality monitoring with machine learning optimization via the XGBoost algorithm, the system outperformed standard human feeding methods. The smart feeding system resulted in a 28% increase in final fish weight (200.33g vs 156.7g), a 30% improvement in feed conversion ratio (1.24 vs 1.76), and a 42% increase in protein efficiency ratio (2.7 vs 1.9), all while maintaining flawless survival rates.
The system's efficiency was further demonstrated by considerable increases in water quality measures, such as 60.7% lower ammonia and 70.5% lower nitrite concentrations in treatment tanks. These findings support the use of AI-IoT integration to solve two main difficulties in intensive aquaculture: feed waste (which can account for up to 70% of production expenses) and water contamination caused by excess nutrients. The edge computing design permitted low-latency modifications without relying on cloud, while the web-based monitoring solution provided practical implementation benefits.

Key advances included the creation of a dynamic feeding model that coupled thermal growth coefficient calculations with real-time environmental monitoring, as well as the implementation of a low-cost, locally manufactured feeding device with a feed accuracy of 96-98%.
This paper presents a scalable approach for precision aquaculture that properly balances production and environmental sustainability.

Future studies should focus on increasing the system's capabilities by integrating more water quality sensors, validating with other fish species, and including behavioral analysis using underwater cameras to further optimize feeding tactics. In conclusion, AI and IoT are poised to revolutionize aquaculture by enabling smarter, data-driven feeding systems.
By optimizing feed delivery, reducing waste, and enhancing sustainability, these technologies address critical challenges in fish farming.
This research contributes to the field by developing an integrated AI-IoT solution that balances productivity and environmental responsibility, paving the way for more efficient and scalable aquaculture practices worldwide. This paper makes an important contribution to smart aquaculture technologies, especially for growing aquaculture economies such as Egypt, which produces 84% of Africa's tilapia. The shown increases in growth performance, feed efficiency, and environmental effect emphasize AI-IoT systems' transformative potential in contemporary aquaculture methods.

Ethical considerations

The experiment was conducted based on the guidelines and obtained the approval of the scientific research ethical committee of Suez Canal University, Ismailia, Egypt .

Consent for publication

All authors gave explicit consent to publish this manuscript.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that supports the findings of this study are available from the corresponding author on request. The data is not publicly available due to privacy or ethical restrictions.

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