Available online at: https://journal.upgripnk.ac.id/index.php/saintek
Jurnal Pendidikan Informatika dan Sains
15(1), 2026, 98-108
E-ISSN: 2407-1536
P-ISSN: 2089-2802

DEVELOPMENT OF AN IOT-BASED AUTOMATIC FISH FEEDING SYSTEM FOR NILE TILAPIA CULTURE IN A RECIRCULATING AQUACULTURE SYSTEM

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Received: 2026-07-12 Accepted: 2026-06-13 Published: 2026-06-30

Abstract

Feed is the single largest cost component in Nile tilapia (Oreochromis niloticus) aquaculture, frequently exceeding 60% of total production costs, yet in most Indonesian smallholder operations it is still dispensed manually by visual estimation. Existing IoT feeders reported in the literature typically automate the timing of feed delivery but do not close the loop on the mass actually dispensed, and they are seldom evaluated inside a Recirculating Aquaculture System (RAS), where uneaten feed directly loads the biofilter. This study addresses that gap by designing, implementing, and empirically evaluating an IoT-based automatic feeder with closed-loop gravimetric dosing, integrated into a RAS unit for Nile tilapia. The system couples an ESP32 microcontroller with a load-cell mass sensor, a servo-actuated feed gate, a BTS7960-driven DC auger, and an RTC scheduling module, and exposes a web interface for real-time adjustment of ration size and feeding schedule. The feeder was benchmarked over ten dispensing cycles at a 50 g target ration, and a rearing trial compared an experimental group (IoT feeder + RAS) with a control group fed manually. Gravimetric dosing achieved a mean absolute error of 2.4% (accuracy 97.6%; mean deviation ±1.2 g per cycle). Over the trial, the experimental group consumed 12.0 kg of feed against 14.0 kg in the control group (a 14.3% reduction) and attained a feed conversion ratio (FCR) of 1.46 versus 2.00. Survival was higher (92.5% vs. 81%), mean individual weight was greater (280 g vs. 245 g), and size uniformity improved (coefficient of variation 8% vs. 15%). The results indicate that adding gravimetric feedback to an IoT feeder, rather than scheduling alone, is what converts automation into measurable feed savings, and that the resulting device is a viable appropriate-technology option for small-scale RAS tilapia producers.

Keywords: automatic fish feeder, ESP32, feed conversion ratio, Internet of Things, Nile tilapia, recirculating aquaculture system

How to cite (in APA style): Rahayu, S., Iqbal, M., Suhartono, R., & Arfian, B. R. (2026). Development of an IoT based automatic fish feeding system for Nile tilapia culture in a recirculating aquaculture system. Jurnal Pendidikan Informatika Dan Sains, 15(1), 98–108. https://doi.org/10.31571/saintek.v15i1.10276

DOI: 10.31571/saintek.v15i1.10276

INTRODUCTION

Nile tilapia (Oreochromis niloticus) is among the fastest-growing aquaculture commodities in Indonesia, favoured for its environmental tolerance, rapid growth, and stable market demand. The profitability of a tilapia operation, however, is governed largely by how well feed is managed (Azhar et al., 2023; Ristanto et al., 2025). Feed routinely accounts for more than 60% of total production cost, so any inefficiency in dosing propagates directly into the margin of the farmer.

In conventional smallholder practice, feed is still broadcast by hand, with both the quantity and the timing estimated visually. This produces three recurring failures: inaccurate ration size, irregular feeding intervals, and uneven spatial distribution of pellets across the tank. The consequences extend beyond wasted feed. Uneaten pellets decompose and degrade water quality, which in turn suppresses growth, widens size dispersion within the cohort, and raises mortality (Lamangkaraka et al., 2024). Manual feeding also ties the operation to continuous human presence, making it difficult to maintain a consistent regime across weekends, night cycles, or multiple tanks (Ahmad & Ashraf, 2025; Rastegari et al., 2023).

The Internet of Things (IoT) offers a route out of this constraint. By networking sensors, actuators, and microcontrollers over a common protocol, IoT allows feeding to be executed on a precise schedule and monitored remotely in real time (Orłowski et al., 2021; Silalahi et al., 2023; Sudibyo et al., 2024). A number of microcontroller-based fish feeders have already been reported. Tiarto et al. (2024) developed a mechanical feeder prototype; Sobri and Topiq (2024) implemented an ESP8266-based feeder with IoT monitoring; Samsumar, et al (2024) and Ariyandi (2025) described comparable Android- and web-controlled designs. Chen et al. (2022) applied IoT instrumentation to water-quality monitoring in fish farms.

Reviewing these systems reveals a consistent limitation. Almost all of them automate when feed is released but not how much is actually released: the ration is inferred from motor run-time or auger revolutions, both of which drift with pellet size, humidity, and hopper fill level. Without a mass-based feedback signal, an "automatic" feeder can dispense a wrong dose with perfect punctuality. A second gap is contextual. Prior evaluations are usually conducted in open ponds or flow-through tanks, whereas in a Recirculating Aquaculture System (RAS) the cost of overfeeding is compounded surplus pellets and the ammonia they generate are loaded straight onto a finite biofilter, so dosing error translates into water-quality failure rather than merely wasted feed.

This study therefore makes two contributions. First, it introduces closed-loop gravimetric dosing into an ESP32-based feeder: a load cell measures the mass actually delivered in each cycle and the controller corrects the actuation until the target ration is met, rather than assuming it. Second, it evaluates the feeder inside a RAS rearing trial on Nile tilapia and reports not only device accuracy but the downstream biological and economic consequences feed consumption, FCR, survival, growth, and size uniformity against a manually fed control. The objective is to determine whether mass-feedback dosing yields feed savings that are measurable at the level of the production cycle, and not merely at the level of the actuator.

METHOD

System development approach

System development followed the Waterfall model (Sommerville, 2016). The model was chosen because the functional requirements of the feeder — scheduled delivery, mass-based dosing, remote configuration — were fully specifiable at the outset, and because its sequential structure produces a documented artefact at each stage, which suits a hardware–software system whose mechanical design must be frozen before firmware can be validated against it. The five phases are shown in Figure 1 and described below.

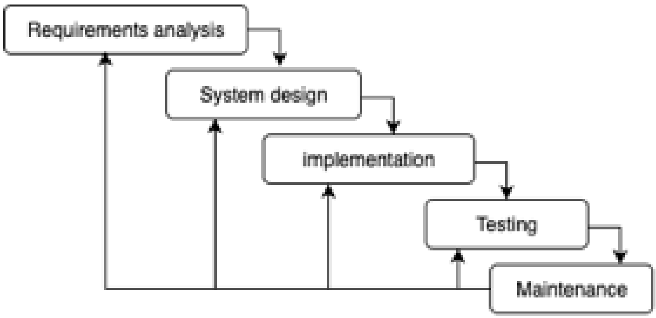

Figure 1. The Waterfall development model (adapted from Sommerville, 2016)

Requirements analysis

Requirements were derived from a literature review of prior automatic feeders and IoT aquaculture deployments, together with observation of manual feeding practice. Functional requirements were defined as: (i) autonomous feed delivery on a user-defined schedule; (ii) dosing specified by mass rather than by run-time; (iii) both manual and automatic control through a web interface. Non-functional requirements covered reliability, ease of use for a non-technical operator, temporal accuracy of scheduling, and stable continuous operation over the rearing cycle.

System design

Hardware design specified an ESP32 as the main controller, a load cell for gravimetric measurement of dispensed feed, a servo motor governing the feed-gate aperture, a DC motor driving the distribution mechanism through a BTS7960 driver, and an RTC module for schedule keeping. Software design covered the control logic, the dosing correction loop, and the web interface. Figure 2 presents the system flowchart, from device initialisation and sensor reading through actuator control to data transmission.

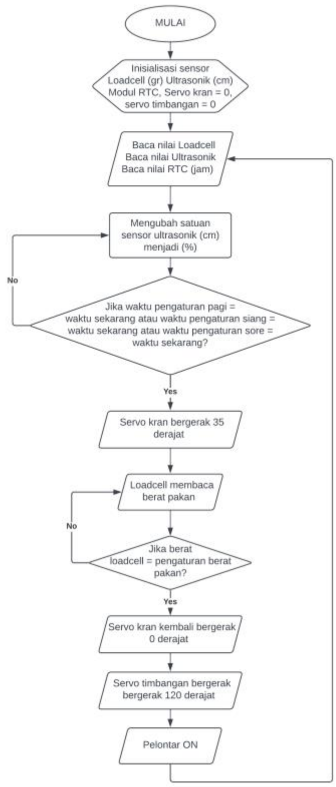

Figure 2. Flowchart of the automatic feeding system

Implementation

Implementation comprised assembly of the mechanical and electronic subsystems and the deployment of firmware to the ESP32 (Sasmito, 2017). The firmware reads the load cell, drives the servo and DC motor, executes RTC-based scheduling, and exchanges data with the web interface over Wi-Fi (Samsumar, et al, 2024).

Testing

Testing verified conformity to the specified requirements (Jaya, 2018) and comprised functional testing, dosing-accuracy testing, and stability testing across repeated feeding cycles. Dosing accuracy was quantified by comparing the mass dispensed by the system against the target mass, measured independently on a digital balance. Scheduling accuracy was verified against the RTC setting.

Maintenance

Post-deployment maintenance consisted of periodic hardware inspection, recalibration of the load cell, and firmware correction where required.

Hardware configuration

The feeder is built around an ESP32 development board, chosen over the ESP8266 used in comparable designs (Sobri & Topiq, 2024) because its dual-core architecture allows the load-cell sampling loop and the Wi-Fi/web-server task to run concurrently without the scheduling jitter that a single-core controller introduces when a blocking network call coincides with a dosing cycle. Feed mass is sensed by a load cell mounted beneath the dispensing mechanism, conditioned by an HX711 24-bit amplifier. A servo motor sets the aperture of the hopper gate, and a DC motor drives the auger that carries pellets from the gate to the discharge chute; the DC motor is commanded through a BTS7960 half-bridge driver, which supplies the stall current the auger draws when a pellet momentarily jams. A DS3231-class RTC module maintains the feeding schedule independently of network availability, so that a Wi-Fi outage suspends remote monitoring but not feeding. Table 1 summarises the components and the function each serves.

Table 1. Hardware components and their functions

Component	Function in the system	Rationale for selection
ESP32 microcontroller	Central controller; executes dosing logic, scheduling, and the embedded web server	Dual-core; integrated Wi-Fi; concurrent sensing and networking
Load cell + HX711	Measures the mass of feed actually dispensed in each cycle	Provides the gravimetric feedback signal
Servo motor	Regulates the hopper gate aperture	Fine positional control of feed release
DC motor + auger	Distributes pellets from gate to discharge chute	Even spatial dispersal of feed
BTS7960 driver	Supplies stable current and torque to the DC motor	Tolerates the stall current of a momentary auger jam
RTC module	Maintains the feeding schedule	Timekeeping independent of network availability

Control logic: closed-loop gravimetric dosing

The dosing routine is the core contribution of the system and is therefore specified here in full. At each scheduled feeding event the controller reads the RTC, tares the load cell against the empty discharge tray, and records the target ration m_target set by the operator through the web interface.

The servo then opens the gate and the DC motor drives the auger while the controller samples the load cell continuously. Dispensing is terminated when the measured mass m_measured reaches m_target, at which point the auger is stopped and the gate is closed. The residual error e = m_measured − m_target for the cycle is logged and transmitted to the web interface.

The distinction from a time-based feeder is that the termination condition is a mass threshold rather than an elapsed interval. In a time-based design the ration is inferred as the product of auger run-time and an assumed mass flow rate, but that flow rate is not constant: it falls as the hopper empties and the head of pellets above the auger decreases, and it varies with pellet size and with ambient humidity, which alters the friction between pellets. The inferred dose therefore drifts away from the intended dose over the course of a hopper fill, and the drift is invisible to the controller. Under gravimetric termination the error is bounded at each individual cycle and cannot accumulate, because every cycle is referenced to a fresh measurement rather than to a stored assumption.

Experimental design and evaluation

Two separate evaluations were carried out: a bench-scale characterisation of the feeder itself, and a rearing trial comparing the feeder against manual feeding.

Dosing accuracy test

Dosing performance was characterised over ten consecutive dispensing cycles at a target ration of 50 g. For each cycle, the mass actually discharged was collected and weighed independently on a digital balance. Deviation was computed as the difference between the discharged and the target mass, and percentage error as the absolute deviation divided by the target mass. System accuracy was reported as 100% minus the mean percentage error. Scheduling accuracy was verified separately by comparing the timestamp of each actuation against the time set on the RTC.

Rearing trial

Production performance was evaluated by comparing an experimental group, reared in a RAS unit and fed by the IoT feeder, against a control group fed manually according to the farm's conventional practice. Both groups were stocked with an initial biomass of 2.0 kg of Nile tilapia. The response variables were total feed administered, initial and final biomass, mortality, feed conversion ratio, mean individual weight at harvest, and the coefficient of variation (CV) of individual weight as an index of size uniformity. FCR was calculated as in Equation (1) and survival rate as in Equation (2):

$$\text{FCR} = \text{total feed administered (kg)} / \text{biomass gain (kg)} \quad (1)$$

$$\text{SR (\%)} = (\text{number of fish harvested} / \text{number of fish stocked}) \times 100 \quad (2)$$

$$\text{CV (\%)} = (\text{standard deviation of individual weight} / \text{mean individual weight}) \times 100 \quad (3)$$

Feed savings were expressed as the percentage reduction in total feed administered by the experimental group relative to the control group. Because the RAS biofilter converts uneaten feed into ammonia load (Crab et al., 2007; Timmons & Ebeling, 2013).

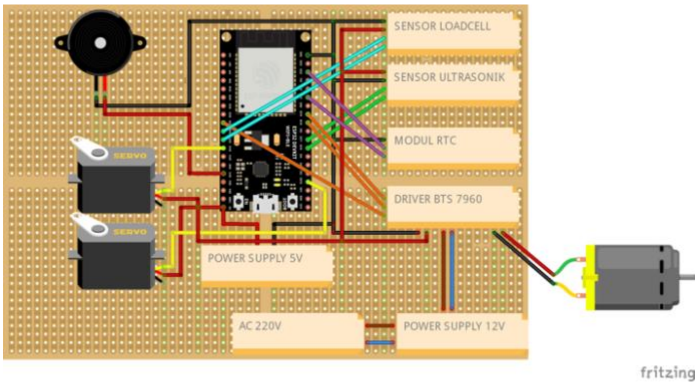

Figure 3. Block diagram of the IoT feeding system

Figure 4. Physical implementation of the automatic feeder unit

RESULTS AND DISCUSSION

System design and realisation

The feeder was realised as an integrated hardware–software unit (Yun et al., 2020). Mechanically, the hopper stores the pellet reserve; a servo motor regulates the gate aperture; a DC motor drives the distribution mechanism; and a load cell, mounted beneath the dispensing mechanism, measures the mass released. The ESP32 acts as the central processing and control node (Ariyandi, 2025), with the BTS7960 driver maintaining stable current and torque to the DC motor during distribution, and the RTC module ensuring that delivery occurs at the scheduled time.

The hopper is mounted on a support frame that keeps the assembly stable during actuation, and the control enclosure housing the ESP32, motor driver, and power supply is fixed to the same frame, which simplifies servicing and keeps wiring runs short. The arrangement is modular, so individual subsystems can be replaced or upgraded without redesigning the whole unit.

On the software side, firmware on the ESP32 integrates load-cell acquisition, motor control, and Wi-Fi communication. The operator can define a feeding schedule for autonomous operation or trigger a manual dose through the web interface shown in Figure 5. Because the ration is expressed in grams rather than in seconds of motor run-time, the same schedule remains valid as the pellet size or hopper level changes.

Figure 5. Web interface of the automatic feeding system

Dosing accuracy of the feeder module

Across ten cycles at a 50 g target, the mean absolute error was 2.4%, corresponding to a mean deviation of approximately ±1.2 g per cycle and an accuracy of 97.6% (Table 2). Errors were distributed on both sides of the target four under-deliveries, three over-deliveries, and three exact hits which is diagnostically important. A time-based feeder that has drifted out of calibration produces error on one side only, because the assumed mass flow rate is either too high or too low. Two-sided, roughly symmetric error of the kind observed here is the signature of a controller that is correcting toward a set point and overshooting slightly, and is therefore evidence that the gravimetric loop is in fact closing. The largest single deviation, 6.0% in cycle 8, is consistent with intermittent pellet bridging in the hopper throat, which momentarily starves the auger; because termination is mass-triggered, that disturbance is absorbed within the cycle rather than carried forward.

Table 2. Feed dispensing test results (target = 50 g per cycle)

Cycle	Target (g)	Dispensed (g)	Deviation (g)	Error (%)
1	50	48	−2	4
2	50	49	−1	2
3	50	51	1	2
4	50	52	2	4
5	50	49	−1	2
6	50	50	0	0
7	50	51	1	2
8	50	47	−3	6
9	50	49	−1	2
10	50	50	0	0
Mean	50	49.6	−0.4	2.4

Error (%) = |deviation| / target × 100. Mean accuracy = 100 − 2.4 = 97.6%.

It is instructive to place this figure alongside the prior generation of feeders. Tiarto et al. (2024) and Sobri and Topiq (2024) both report functionally successful prototypes, and Samsumar, et al (2024) and Ariyandi (2025) describe comparable web- and Android-controlled units; but in each case the reported performance metric is whether the device fired at the scheduled time and whether the interface responded, not how closely the delivered mass matched the intended mass. That is not an oversight on the part of those authors so much as a consequence of the architecture: a feeder without a mass sensor has no means of reporting its own dosing error, because it has no observation of the quantity it is supposed to be regulating. The present system can report an error of 2.4% precisely because it measures the variable it controls. The contribution here is thus less a matter of achieving a better number than of making the number observable at all which is the precondition for any subsequent optimisation of the ration.

The practical significance of a 2.4% dosing error becomes clear when it is projected across a production cycle. At three meals per day, a systematic overfeed of even 5% compounds into tens of kilograms of surplus feed over a grow-out, all of which is both a purchased input that produced no fish and an organic load that the biofilter must process.

Feed efficiency and waste reduction

The experimental group consumed 12.0 kg of feed over the trial against 14.0 kg in the manually fed control, a reduction of 14.3%. Biomass gain moved in the opposite direction: 8.2 kg in the experimental group against 7.0 kg in the control. The combination produced an FCR of 1.46 for the IoT-RAS group versus 2.00 for the control (Table 3) that is, the automated group converted feed into fish flesh roughly 27% more efficiently while consuming less of it.

Table 3. Feed efficiency of the experimental and control groups

Parameter	Experimental (IoT + RAS)	Control (manual)
Total feed administered (kg)	12	14
Initial biomass (kg)	2	2
Final biomass (kg)	10.2	9
Biomass gain (kg)	8.2	7
Mortality (%)	6	15
FCR (feed / biomass gain)	1.46	2

Both FCR values fall within the range reported for Nile tilapia in the literature, which lends the comparison credibility. The systematic review by Mengistu et al. (2020) identifies feeding rate as the management variable with the largest single effect on growth and feed conversion in this species, ahead of stocking density and study length; a control FCR near 2.0 is typical of ration-imprecise pond practice, while values in the range of 1.4–1.6 are characteristic of controlled, ration-matched regimes. The present result is therefore not an outlier claim but an instance of a well-established dose–response relationship, obtained here through automation rather than through manual precision.

The causal mechanism is worth stating explicitly, because it is what distinguishes this study from a simple demonstration that automation works. Under manual feeding the operator cannot observe how much feed has actually been consumed, and rationally hedges against underfeeding which visibly stunts the crop by erring toward generosity, which does not visibly do anything at all. The surplus sinks, decomposes, and never enters fish biomass. Gravimetric dosing removes that asymmetry of information: the ration delivered is the ration intended, and the operator is no longer paying an insurance premium in feed for an uncertainty that no longer exists. This reframes the 14.3% saving not as a mechanical efficiency but as the elimination of a behavioural safety margin.

In a RAS the consequence is compounded. Uneaten pellets are not merely a financial loss; they are a nitrogen input. Total ammonia nitrogen in a recirculating system originates both from the fish's own protein metabolism and from the microbial decomposition of uneaten feed and organic matter, and the resulting load must be oxidised by a biofilter of finite nitrifying capacity (Crab et al., 2007; Timmons & Ebeling, 2013). Because ammonia production scales with feed input, a chronically overfed RAS drives its biofilter toward and past its design load, at which point total ammonia nitrogen accumulates, unionised ammonia rises, and the fish are exposed to a chronic stressor. Overfeeding in a RAS is thus self-punishing in a way it is not in a flow-through pond, and this is precisely why a feed-dosing intervention should be expected to yield a larger benefit in RAS than the pond-based literature would predict. The mortality difference observed here (6% versus 15%) is consistent with that mechanism, and the survival figure in the experimental group is close to what Mengistu et al. (2020) associate with well-managed dissolved-oxygen and water-quality conditions.

Growth, survival, and size uniformity

Survival in the experimental group reached 92.5%, against 81% in the control. Mean individual weight at harvest was 280 g versus 245 g. Size uniformity also improved: the coefficient of variation of individual weight was 8% in the experimental group against 15% in the control, indicating a narrower weight distribution within the cohort.

The uniformity result deserves closer attention than it usually receives, because it is the variable most directly attributable to distribution rather than to dose, and it therefore isolates a distinct mechanism. Size heterogeneity in tilapia is understood to arise from two sources: non-interactive variation, which is genetic and developmental, and interactive variation, which is generated by competition and social dominance within the cohort (Kestemont et al., 2003, as discussed in the compensatory-growth literature). Only the interactive component is amenable to management. Azaza et al. (2013) showed that rearing conditions which intensify competition high stocking density in monosex male Nile tilapia increase both size heterogeneity and inter-individual variation in feed intake, the two being linked: fish that monopolise feed grow faster, and fish that grow faster monopolise feed more effectively, a positive feedback that widens the weight distribution of a cohort that began uniform.

Hand-broadcast feed feeds exactly this loop. Pellets land in concentrated patches that dominant individuals defend, so access to feed becomes a function of social rank rather than of hunger. Even, scheduled, mechanically dispersed delivery flattens the spatial gradient in feed availability and so weakens the advantage that dominance confers. The halving of the coefficient of variation observed here (8% versus 15%) is consistent with a reduction in the interactive component of heterogeneity, and is not explicable by ration accuracy alone a perfectly dosed but badly distributed meal would still be captured unevenly.

The consistent regularity of the automated schedule is likely to contribute as well. Feeding-frequency studies in Nile tilapia find that more frequent and regular meals improve weight gain and reduce the water-quality burden of a single large ration (Fava et al., 2022), and an automated feeder delivers the prescribed frequency reliably across weekends and night cycles, whereas a human operator does not. The practical value of the uniformity gain is commercial rather than merely biological: a uniform cohort can be harvested and graded in a single pass, reduces the labour of size-sorting, and commands a more consistent price at market.

Limitations

Several limitations qualify these findings. The rearing trial compared a single experimental unit with a single control unit, so tank-level effects cannot be separated from treatment effects, and the differences reported here should be read as indicative rather than as statistically established. Dosing accuracy was characterised at one ration size (50 g) and with one pellet grade; performance at smaller rations, where the same absolute deviation represents a larger percentage error, was not established. The trial covered one production cycle in one facility, so seasonal and site effects are unaddressed. Finally, the ration remained operator-set: the system delivers accurately what it is told to deliver, but does not yet adjust the ration to standing biomass or to observed feeding response.

CONCLUSION

This study designed, implemented, and evaluated an IoT-based automatic feeder with closed-loop gravimetric dosing, integrated into a recirculating aquaculture system for Nile tilapia. Integrating an ESP32 controller, a load cell, a servo-actuated gate, a BTS7960-driven DC motor, and an RTC module produced a feeder that dispenses a specified ration by mass rather than by elapsed time, achieving 97.6% dosing accuracy with a mean error of 2.4% over ten cycles.

In the rearing trial, this translated into a 14.3% reduction in feed consumed, an FCR of 1.46 against 2.00 under manual feeding, higher survival (92.5% versus 81%), greater mean weight (280 g versus 245 g), and improved size uniformity (CV 8% versus 15%). The evidence supports the central claim of the paper: it is mass feedback, not scheduling alone, that converts feeder automation into feed savings that survive to the level of the production cycle.

The system is inexpensive, modular, and operable from a browser, and is therefore a plausible appropriate-technology option for small-scale RAS tilapia producers. Subsequent work should replicate the trial with multiple tanks and formal statistical testing, extend the dosing characterisation across ration sizes and pellet grades, and close a second control loop by adapting the ration to standing biomass or to water-quality telemetry.

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