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Data-Driven Insights in Patin Fish Farming Based on a Six-Month Analytical Study of Biomass Feeding Efficiency and Profitability

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ABSTRACT

This study explores how real-world data and smart farming tools, specifically the iSENSfishery system, can enhance small-scale Patin fish farming in Malaysia. Over a six-month period, data on fish growth, feeding activity, water quality, and farm economics were collected and analyzed. Using IoT sensors and the iSENSfishery dashboard, farmers monitored key parameters to reduce feed waste and make informed decisions. Correlation analysis revealed strong links between feeding patterns, biomass gain, and economic performance. Statistical analysis further uncovered how mortality and dissolved oxygen levels affected fish survival. The system helped achieve an ROI of over 170%, supported by stable water quality and structured feeding. By combining technology with practical farming needs, iSENSfishery offers a scalable, affordable solution for rural aquaculture. This study highlights its potential to empower farmers through data, improve sustainability, and support smarter decision-making in everyday operations.

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1. INTRODUCTION

In Malaysia, food security partly depends on the aquaculture sector, which supports the rural economy, particularly in regions such as Pekan, Pahang [1]. One of the most economically important freshwater species is Pangasius hypophthalmus, commonly known as Patin. It is widely farmed in the states of Pahang, Perak, Terengganu, and Johor, with Pekan and Temerloh often regarded as the "Patin Capitals" of Malaysia due to their long-standing tradition and high production volume. Patin farming is typically conducted in fibre ponds, concrete tanks, and increasingly, in floating cages along rivers such as the Pahang River. The species is favored for its adaptability, rapid growth, and strong market demand both locally and for export [2].

Small and medium-scale farmers still rely on manual farming operations, which presents significant challenges in terms of productivity and efficiency [3][4]. The challenges include feed management, water quality fluctuations, disease outbreaks, and a general lack of digital tools to support decision-making [5]. Overfeeding not only leads to high operational costs but also contributes to environmental degradation, while underfeeding stunts fish growth and increases mortality risk. Furthermore, water quality fluctuations—especially in river cage systems—can cause sudden stress or disease outbreaks, further reducing productivity.

Most small-scale fish farmers still rely on manual monitoring and experience-based decision-making, often passed down through generations. While this approach has historical merit, it is increasingly insufficient in dealing with modern-day challenges such as climate change, unpredictable weather patterns, and rising feed costs. Decisions related to feeding, harvesting are frequently made based on intuition rather than data, which can lead to inefficiencies, lower yields, and financial loss.

To ensure the long-term viability of the aquaculture sector, there is a growing need to transition toward data-driven, evidence-based approaches [6]. Smart technologies like water quality sensors, feeding monitors, and data dashboards can empower even smallholder farmers with real-time insights into their farming environment. These tools allow for more accurate forecasting, early detection of anomalies, and better decision-making to improve operational efficiency and farm resilience.

In recent years, the integration of Internet of Things (IoT) technologies, machine learning (ML), and data analytics has begun to transform aquaculture operations globally [7]. IoT devices such as sensors and camera systems enable continuous monitoring of key parameters including temperature, pH, dissolved oxygen, turbidity, and feeding behavior. This real-time data forms the basis for predictive analytics and decision support systems.

Recent studies are showing how machine learning and computer vision are starting to transform the way we understand fish behavior and environmental conditions [8][9][10]. For example, in [11], convolutional neural networks (CNNs) has been used to predict river flow in human impacted system. In another case, in [12] the study combined weather and water sensor data in a smart hybrid model to predict ammonia levels and optimize feeding routines. At the same time, user-friendly data dashboards are emerging, offering farmers insights into trends like biomass growth and feed efficiency. These tools can make day-to-day decisions easier and long-term planning smarter. But there's still a catch—many of these technologies are stuck in the pilot phase. They're not yet reaching smallholder farmers, mainly because of infrastructure challenges, high costs, or the technical skills required to use them.

Even with all the exciting progress, a clear gap remains: we still need practical, affordable, and easy-to-use systems designed specifically for small and medium-scale fish farmers in Southeast Asia. Most of the current models assume access to advanced infrastructure and aren't tailored for real-world conditions on the ground. Local factors—like weather patterns, native fish behavior, and traditional farming methods—are often left out of the equation, making it harder for farmers to adopt these tools in a meaningful way [13] [14].

To address the operational challenges faced by small-scale fish farmers, we developed a smart aquaculture management system tailored for traditional farming communities in Pekan, Pahang. This system adopts a data-centric approach by collecting and analyzing key parameters such as water quality (temperature, pH, and dissolved oxygen), feeding activity (pellet input and missed feedings), and fish performance indicators (biomass, growth rate, and mortality). By integrating IoT sensors with real-time data analytics, the system empowers farmers to continuously monitor, analyze, and act on operational insights—enabling them to reduce feed wastage, lower costs, and improve overall farm productivity.

This paper presents a six-month analytical study based on real aquaculture data collected from the deployment of the iSENSFishery system at a floating cage facility in Padang Rumbia, Pahang. One cage was selected as a case study, stocked with 2,500 Patin fish (Pangasius hypophthalmus), and managed under typical small-scale farming conditions. The system was installed at the start of a new production cycle in July 2024, allowing continuous data collection across various performance indicators, including biomass growth, feed conversion ratio (FCR), mortality trends, and economic performance.

The objective of this study is to demonstrate how data analytics, when implemented in a practical and accessible manner, can significantly enhance aquaculture decision-making. By enabling real-time monitoring and data-driven adjustments, the system provides a scalable, cost-effective solution designed to meet the needs of rural aquaculture operations. It not only supports day-to-day management but also contributes to long-term sustainability and profitability for smallholder fish farmers.

To summarize, this study addresses a critical gap in smart aquaculture by developing an integrated hardware-software system—iSENSfishery—that enables real-time monitoring and decision-making for Patin fish farming. While several IoT-based aquaculture systems exist, few provide a holistic, data-driven approach tailored to Malaysia's aquaculture context. The main objective is to design a system capable of collecting key water quality parameters and fish behavior data, transmitting them to the cloud, and enabling AI-based analytics. Our findings demonstrate the feasibility of real-time monitoring and show improved data accuracy and system responsiveness. However, limitations include a relatively short deployment period and limited scale of pilot testing. Future work will focus on large-scale field validation, enhanced predictive models, and cost optimization for wider adoption by smallholder fish farmers.

2. METHOD

This study took a step-by-step, data-driven approach to better understand how a small-scale Patin fish farm performs—both biologically and financially—based on real-world data collected over a production cycle. We began with basic statistical analysis to get a feel for the dataset and identify patterns in fish growth, feeding, and environmental conditions. Next, we explored the relationships between different variables through correlation analysis, helping us see how factors like water quality or feeding might influence fish health and performance. From there, we looked at the economic side—calculating key metrics such as profitability, cost breakdowns, and return on investment (ROI). Each part of the analysis built on the previous one, moving from general observations to more focused insights. Taken together, this approach provided a well-rounded understanding of both the technical and financial aspects of the farming operation, with the goal of helping smallholder fish farmers make more informed, data-backed decisions.

2.1. Data Collection Parameters

This study is based on real-world data collected from a six-month deployment of the iSENSfishery smart aquaculture system at a floating cage facility in Padang Rumbia, Pahang, Malaysia. The system was installed in July 2024, during the fry stage of 2,500 Patin fish (Pangasius hypophthalmus), and operated continuously until the end of the grow-out phase in December 2024. The aim of the deployment was to monitor environmental conditions, feeding activity, fish growth, and farm economics in real-time, enabling a comprehensive evaluation of smart farming effectiveness in a rural aquaculture setting.

The system recorded data at hourly intervals, resulting in 43,200 time-stamped entries per parameter. Multiple integrated sensors and manual recording modules were used to collect a range of biological, environmental, operational, and economic parameters. These data served as the basis for analyzing key performance metrics such as biomass growth, feed conversion ratio (FCR), mortality trends, and economic viability. The dataset includes both continuous sensor readings and manually logged operational data. The parameters were selected based on their relevance to aquaculture performance monitoring and their impact on overall productivity and profitability.

The iSENSfishery system as shown in figure 1 is an automatic fish feeding solution developed to address the inefficiencies and labor-intensive nature of traditional feeding practices in small- and medium-scale aquaculture. Designed with a focus on rural fish farms, the system integrates mechanical, electrical, electronic, and software components into a single, intelligent platform that supports automation, monitoring, and data analytics. Figure 2 shows the dashboard of the iSENSfishery system.

Figure 1. Automatic feeding system, integrated as a core component of the iSENSfishery smart aquaculture platform.

For the iSENSfishery, the system consists of a feed hopper connected to a motorized screw conveyor or paddle mechanism that precisely dispenses pelletized feed into the water. The feed delivery is uniform and scheduled according to fish growth stages and appetite, with pellet sizes ranging from 3 mm to 5 mm over the production cycle. The mechanical structure is housed in a weatherproof, corrosion-resistant casing to suit outdoor aquaculture environments such as river cages and earthen ponds. The electrical design of the iSENSfishery operates on a 12V or 24V DC system, powered either by solar panels with battery backup or through a stabilized AC connection. This low-voltage setup ensures energy efficiency and safety in remote deployment. The electronics are managed by a microcontroller—such as an ESP32 or Arduino-based board—that automates the feeding schedule, manages motor control, and communicates with sensors installed in the system.

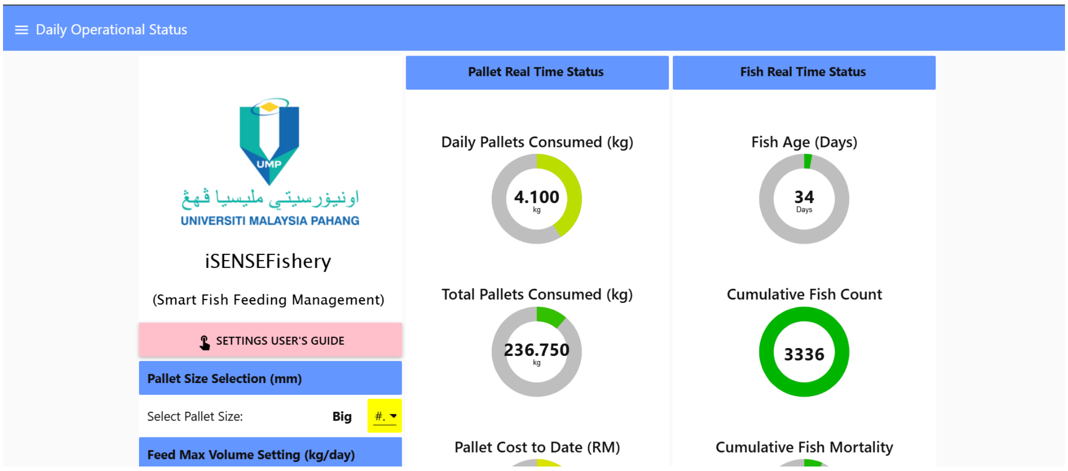

Figure 2. The iSENSfishery dashboard, which provides real-time visualization of key aquaculture parameters such as water quality, feed usage, fish growth, and mortality trends.

Instrumentally, the iSENSfishery is equipped with various sensors to ensure reliable operation. These include load sensors to monitor feed quantity in the hopper, vibration or current sensors to confirm feed release activity, and optional environmental sensors to detect water parameters such as temperature, pH, and dissolved oxygen. Sensor data is collected in real time and processed by the microcontroller before being uploaded to a cloud-based platform.

A key feature of the iSENSfishery system is its Internet of Things (IoT) integration. Using Wi-Fi or 4G cellular modules, the system transmits data to the cloud where it is stored and made accessible through a web dashboard or mobile application. This cloud connectivity allows users to monitor feeding activities, update feeding schedules remotely, and receive real-time notifications in the event of irregularities, such as missed feedings or low hopper levels.

The iSENSfishery software platform (figure 2) includes a user-friendly dashboard that presents analytics on feed usage, fish biomass estimates, feed conversion ratios, and operational costs. Through this dashboard, farmers can gain insight into trends, optimize their feeding plans, and make informed decisions to improve productivity and profitability. The mobile application further enhances accessibility, allowing farmers to manage feeding routines and monitor system status from anywhere.

2.2. Data Structure and Context

The dataset structure as shown in table 1 supports a rich analysis of time-dependent interactions between environmental conditions, feeding behavior, and fish performance. The dataset is structured in a relational time-series format, stored and accessed via the iSENSfishery cloud dashboard. Each parameter is linked by timestamp, allowing synchronized analysis of feeding behavior, environmental changes, and fish response.

Table 1. Parameters Collected in the iSENSfishery System Deployment

Parameter	Unit	Type	Description
Fish weight	grams	Manual (weekly)	Average weight of sampled fish; used to estimate biomass growth.
Pellet size	mm	Manual	Pellet diameter adjusted during grow-out phase (3 mm to 5 mm).
Feed quantity	grams/day	Semi-auto	Daily amount of feed given; verified by feeder logs and manual input.
Water temperature	°C	Sensor (hourly)	Measured using in-situ sensor; fluctuates based on time of day and weather.

Parameter	Unit	Type	Description
Dissolved oxygen (DO)	mg/L	Sensor (hourly)	Indicates oxygen availability; critical for fish health.
pH level	–	Sensor (hourly)	Measures water acidity; stable range between 6.5–8.2.
Mortality count	fish/day	Manual	Number of fish mortalities observed and removed daily.
Survival rate	%	Calculated	Percentage of fish alive over time relative to initial stock.
Feed cost	MYR/day	Calculated	Cost computed from feed type, quantity, and unit price.
Harvest value (projected)	MYR	Calculated	Projected revenue from fish sales based on weight and market price.
Feed Conversion Ratio (FCR)	–	Calculated	Feed given (kg) divided by weight gain (kg); key efficiency indicator.

This dataset forms the foundation of the analysis presented in this paper, supporting a range of insights into fish growth, environmental dynamics, operational efficiency, and data-driven decision-making for sustainable Patin aquaculture. Sensor data such as temperature, dissolved oxygen, and pH were captured with minimal latency and synchronized with operational logs such as feed delivery and mortality records.

This level of detailed data makes it possible to explore meaningful patterns over time—for example, identifying how drops in dissolved oxygen (DO) might align with periods of missed feeding or sudden increases in fish mortality. Such insights not only help farmers understand what's happening on the farm but also open the door to predictive tools that support more proactive, responsive management.

2.3. Hardware Description

The iSENSfishery system comprises several integrated components designed for real-time water quality monitoring and decision support in aquaculture environments. The core hardware architecture includes a **sensor node**, **microcontroller**, **communication module**, and **cloud gateway**.

- **Sensor Node**: Collects multi-parameter environmental data (e.g., pH, dissolved oxygen, ammonia, temperature).
- **Microcontroller (e.g., ESP32/Arduino)**: Processes raw sensor readings and prepares them for transmission.
- **Communication Module**: Transmits data to the cloud using Wi-Fi or LoRa, depending on the deployment scenario.
- **Power Supply**: A solar-powered battery setup ensures continuous operation.
- **Cloud Gateway & Dashboard**: The data is sent to a central cloud platform for storage, analytics, and visualization via a user-friendly dashboard.

This setup ensures robust, low-power, and scalable data acquisition suitable for deployment in both remote and semi-urban aquaculture sites.

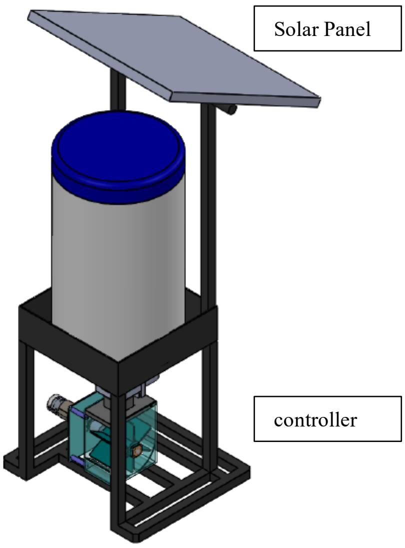

Figure 3. The diagram of the iSENSfishery automated feeder system, showing the integration of the feed container, motorized dispensing unit, microcontroller, real-time clock module, and communication interface for scheduled and remote feeding operations

3. DATA ANALYSIS METHODS

3.1. Statistical Summary

As the first step in the data analysis, statistical techniques were applied to better understand the structure and behavior of the dataset. These descriptive methods helped summarize the central tendency, variability, and distribution of key aquaculture variables, forming a solid foundation before moving on to more complex analysis [15]. The variables explored at this stage included indicators of fish growth (such as individual fish weight and total biomass), feeding behavior (daily and total pellet consumption, as well as missed feeding events), cost-related metrics (pellet cost and fry cost), mortality records (both hourly and cumulative), and environmental conditions (temperature, pH, and dissolved oxygen).

For each parameter, standard statistical measures—mean, minimum, maximum, and standard deviation—were calculated. These values provided insights into the typical range of each variable and helped flag any unusual patterns or outliers. To simplify the analysis and make trends easier to interpret, the original hourly dataset was aggregated into daily intervals. Continuous variables were averaged across each day, while discrete variables such as mortality counts were summed. This transformation reduced data complexity while still preserving key daily trends, setting the stage for the deeper correlation, event, and performance analyses that followed. Lastly, to prepare for further analysis involving derived metrics such as Feed Conversion Ratio (FCR), biomass was computed based on the product of average fish weight and surviving population at each time interval [16]. Mathematically, biomass $B(t)$ was defined as:

$$B(t) = \frac{W(t)}{1000} \times S(t) \qquad (1)$$

S(t) is the number of surviving fishes at the same time. This equation converts fish weight to kilograms and aggregates it across the surviving population to estimate the total biomass present in the system.

3.2. Economic Metrics

To understand how well the fish farming operation performed financially, we looked at a set of key economic indicators. These included the costs of inputs like feed and fry, the amount of fish biomass produced, and the expected market price at harvest. The goal was to get a clear picture of profitability over time, see how much each cost component contributed to overall expenses, and calculate the return on investment (ROI) for the entire six-month farming cycle. Profit was modeled as a cumulative metric over time, representing the net revenue from surviving biomass at each time point after deducting all production costs. Mathematically, cumulative profit P(t) at time t was computed as:

$$P(t) = B(t).M - (C_{fry} + C_{feed}(t)) \qquad (2)$$

where B(t) is the adjusted biomass (kg) at time t, M is the fish market price per kg, Cfry is the fixed cost of fry, and Cfeed is the accumulated pellet cost up to time t.

To understand how different inputs contribute to overall production cost, a cost breakdown was performed. The total cost was divided into two primary components: (i) the initial fry cost and (ii) the cumulative pellet cost. This breakdown enabled analysis of which input dominated operational expenses and how cost allocation shifted over time. Pellet cost was calculated dynamically using the total amount of feed consumed and the fixed cost per kilogram of feed:

$$C_{feed}(t) = P_{kg}.F(t) \qquad (3)$$

where Pkg is the pellet price per kg and F(t) is the total feed consumed up to time t. The Return on Investment (ROI) was also computed periodically to track financial efficiency throughout the farming period. ROI was calculated either weekly or monthly using the following formula:

$$ROI(t) = \left(\frac{P(t)}{C_{fry}+C_{feed}(t)} \times 100\right) \qquad (4)$$

This metric provides a normalized percentage that reflects the profitability relative to total cost invested at any point in time. Tracking ROI over time helped identify specific phases of the farming cycle where operational efficiency improved or declined, which is valuable for optimizing harvest timing and cost control.

3.2. Correlation Analysis

To investigate the interdependencies between environmental conditions, feeding behavior, and fish performance, correlation analysis was conducted using multiple variable pairs drawn from the dataset. The objective was to explore whether statistically significant relationships existed that could explain variations in fish mortality, growth, and overall production efficiency.

One of the primary correlations examined was between dissolved oxygen (DO) levels and fish mortality. Given the well-established importance of DO in aquatic health, this analysis aimed to determine whether declines in DO were consistently associated with increased hourly or daily mortality events. By comparing time-aligned values of DO and mortality, the analysis helped identify critical thresholds where low oxygen levels may become detrimental to fish survival. In addition, the relationship between feed input and biomass gain was analyzed to evaluate the efficiency of feeding practices. This involved correlating the total or daily feed provided with changes in adjusted biomass over time. A strong positive correlation in this context would suggest that feeding levels were closely aligned with fish growth, whereas a weak or inconsistent relationship might indicate suboptimal feeding practices, feed wastage, or biological inefficiencies.

The third correlation explored was between fish weight and water quality parameters, specifically temperature, pH, and DO. This analysis was aimed at understanding whether water conditions played a measurable role in influencing growth rates. By tracking fish weight progression alongside environmental fluctuations, the analysis offered insight into how tightly fish growth is linked to habitat stability. To account for both linear and non-linear relationships, two statistical techniques were applied: Pearson correlation and Spearman rank correlation. Pearson correlation measures the strength and direction of a linear relationship between two continuous variables. It assumes that the data are normally distributed and that the relationship is linear across the range of values. This method is sensitive to outliers and may underperform in the presence of skewed data or non-linear associations.

4. RESULTS AND DISCUSSION

Table 2 presents the descriptive statistics for core aquaculture variables over the six-month farming period. The analysis includes the mean, minimum, maximum, and standard deviation of fish weight, biomass, feed consumption, and water quality indicators. The average fish weight was approximately 900 g, with a wide range reflecting growth across the cycle. Biomass showed substantial variability due to mortality and feeding behavior, while dissolved oxygen and temperature remained within stable ranges. These descriptive metrics provided a baseline for trend identification and guided the subsequent correlation and predictive analysis.

Table 2. Statistical data for the 6 months farming

Parameter	Mean	Min	Max	Standard Deviation
Fish Weight (g)	901.5778	200.7	1100	274.1501
Biomass (kg)	712.1373	6.7446	2128	584.4052
Daily Pellet Consumption (kg)	4.666667	3	6	1.374528
DO (mg/L)	6.798553	6.13	7.51	0.198721
Temp (Â°C)	27.99188	26.2	29.9	0.498027
pH	7.497752	7.21	7.84	0.099538
Hourly Deaths	0.086806	0	2	0.294445

4.1. Fish Growth and Biomass Performance

Over the six-month grow-out period, the average fish weight steadily increased, culminating in a final mean weight of approximately 901 grams per fish. The growth trajectory exhibited a gradual increase during the early stages of cultivation (Month 1 to Month 3), likely due to metabolic adaptation and initial feeding stabilization. This was followed by a period of accelerated weight gain in the final months (Month 4 to Month 6), consistent with typical growth patterns observed in Pangasius hypophthalmus production cycles.

Figure 3 illustrates the daily progression of average fish weight throughout the six-month grow-out period. The trend shows a consistent upward trajectory, with natural daily fluctuations that are characteristic of the data at the Padang Rumbia cage. These variations reflect the typical biological responses of fish to feeding regimes, environmental conditions, and metabolic activity.

Parallel to the increase in fish weight, the total biomass in the system—calculated from the average weight of individual fish and the number of surviving fish—also showed a steady rise, as depicted in Figure 4. By the end of the cycle, the total biomass reached approximately 2,100 kilograms. The biomass curve closely aligns with the fish weight trajectory, indicating that weight gain was supported by a stable survival rate. The minor dips and variations observed in the biomass trend are consistent with realistic production dynamics, where mortality events, feed intake variations, and environmental changes contribute to short-term fluctuations in yield.

Figure 5 displays the number of surviving fish over time. The population declined gradually due to natural mortality, with no extreme drops or spikes. The final population at harvest was approximately 2,121 fish, representing a cumulative mortality rate of 15%. This survival pattern suggests that losses occurred in a distributed manner rather than as the result of isolated mortality events, which allowed biomass accumulation to continue uninterrupted.

Together, these growth and survival indicators confirm the biological viability and operational stability of the farming system. The alignment between weight gain, biomass accumulation, and steady survival reinforces the conclusion that the environmental and feeding conditions maintained during the production cycle were effective in supporting consistent fish development and overall system performance.

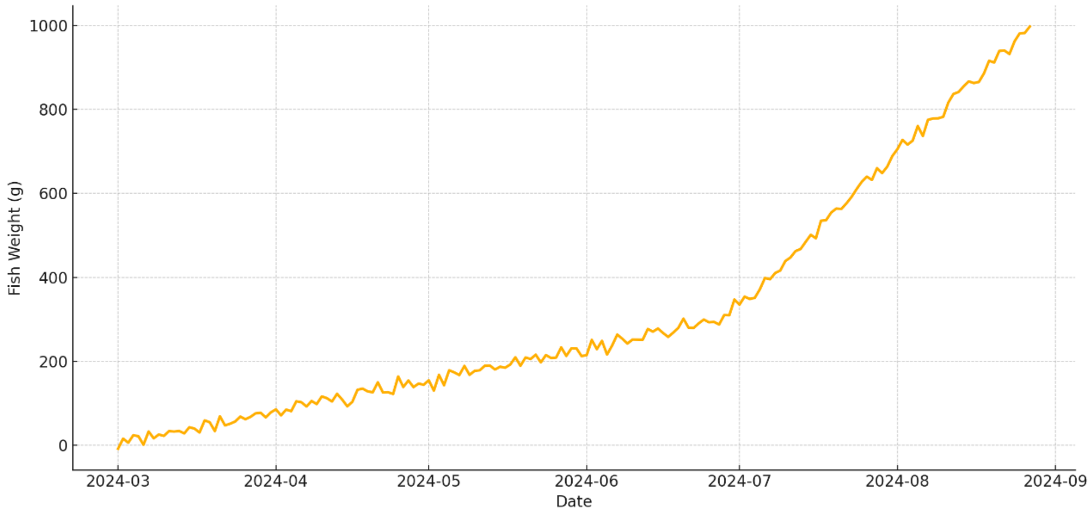

Figure 3. Fish weight growth over six months

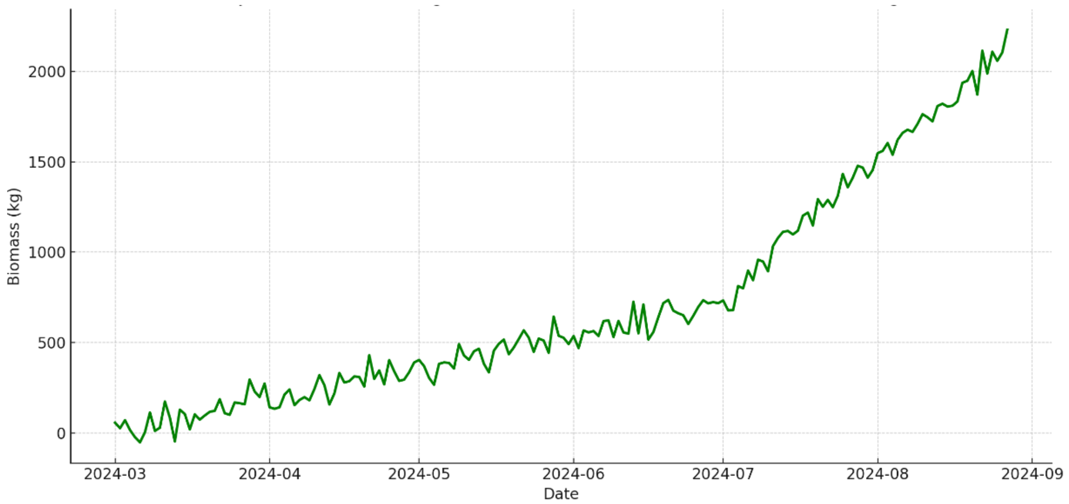

Figure 4. Biomass progession over six months

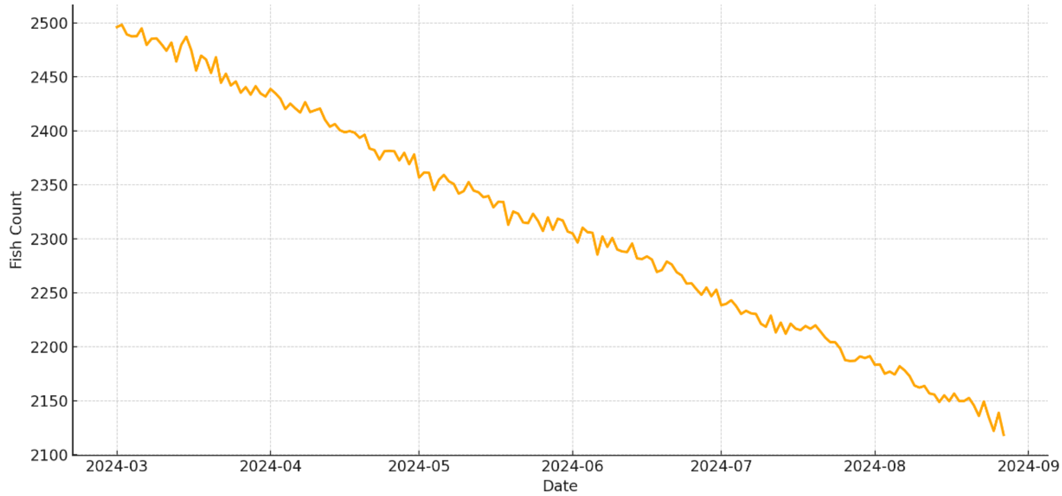

Figure 5. Surviving fish population over sixt months

4.2. Feed Utilization, Efficiency, and Economic Performance

Feed management throughout the production cycle followed a structured regime that was scaled according to fish growth stages. In the early phase (Month 1 to Month 3), the daily pellet allocation was maintained at 4 kg per day to meet the nutritional needs of the juvenile fish. As fish transitioned into a rapid growth phase (Month 3 to Month 6), the feeding rate increased to 6 kg per day. In the final grow-out period approaching harvest (Month 6 to Month 8), feeding was further increased to 10 kg per day, supporting final weight gain and maximizing harvest biomass.

Over the full six-month monitoring period, the average daily pellet consumption was 4.83 kg, with a total feed usage of 3,290 kg. This consumption trend aligned well with expected biomass requirements at each growth stage. Figure 4 illustrates this increasing trend in daily feed usage, which closely mirrors the phase-based feeding plan. Feed conversion ratio (FCR) was used to evaluate how efficiently feed was transformed into biomass. The calculated FCR for the full cycle was 1.56, meaning that 1.56 kg of feed was required to generate 1 kg of fish biomass. This value is well within accepted standards for commercial aquaculture and reflects efficient feed utilization. As shown in Figure 5, FCR remained stable across the farming cycle, even with increased feed input in the later stages, suggesting that higher feeding levels did not negatively impact feed efficiency.

Economically, the pellet cost was recalculated using the updated market price of RM3.20 per kg, leading to a total feed cost of RM10,528. Combined with the fry cost of RM1,000, the overall operational cost reached RM11,528. At the point of harvest, a total of 2,100 kg of biomass was produced and sold at RM15.00 per kilogram, yielding a gross revenue of RM31,524. This resulted in a net profit of RM19,996 and a Return on Investment (ROI) of approximately 173.5%.

4.3. Correlation Insight

Correlation analysis was conducted using both Pearson and Spearman methods to evaluate the strength of relationships among key variables. Comparison between these 2 methods is shown in the table 3. The Pearson correlation revealed a moderate negative association between DO and mortality, suggesting that lower DO levels were generally linked with increased fish deaths. Similarly, a strong positive correlation was observed between fish weight and adjusted biomass, indicating consistent weight gain across the surviving population. Spearman correlation confirmed these trends and also revealed slightly stronger monotonic associations, particularly in non-linear patterns between environmental parameters and performance metrics.

The correlation between dissolved oxygen (DO) and hourly fish deaths was found to be weak under both methods. The Pearson correlation coefficient was 0.011, while Spearman's was 0.006, indicating a very low association. This suggests that no strong or consistent relationship was detected between DO levels and mortality across the entire cycle. While DO is known to influence fish survival in extreme conditions, in this dataset, DO levels may have remained mostly within safe ranges, limiting any detectable impact.

A perfect positive correlation (1.000) was observed between average fish weight and biomass under both Pearson and Spearman methods. This was expected, as biomass is directly calculated from fish weight and surviving population. The result confirms the internal consistency of the data and validates biomass as a reliable indicator of production volume. The correlations between DO and fish weight, as well as DO and biomass, were also extremely weak, with both Pearson and Spearman coefficients near 0.002–0.006. These results imply that DO fluctuations did not significantly influence growth trends in this dataset, likely because DO levels were managed within optimal thresholds throughout the production period.

Table 3. Comparison of correlation methods.

Variable Pair	Pearson	Spearman	Interpretation
DO vs Hourly Deaths	0.011	0.006	Very weak, no significant relationship
Fish Weight vs Biomass	1.000	1.000	Perfect positive, as expected
DO vs Fish Weight	0.002	0.006	Negligible relationship
DO vs Biomass	0.002	0.006	Negligible relationship

The comparative analysis between Pearson and Spearman coefficients confirms the robustness of findings. In all cases, both methods yielded consistent interpretations—particularly affirming the absence of strong linear or monotonic relationships between DO and biological variables in this cycle. This reinforces the conclusion that water quality was well-managed and did not act as a limiting factor during the observation period.

The heatmaps in Figures 6 and 7 visualize the correlation strength between key aquaculture variables. Both Pearson and Spearman methods consistently show a perfect positive correlation between fish weight and adjusted biomass, confirming the direct mathematical and biological relationship between these variables. In contrast, dissolved oxygen (DO) shows negligible correlation with both mortality and fish growth, with coefficients close to zero in both analyses. This indicates that DO levels remained within acceptable ranges throughout the production cycle, with no significant impact on fish performance or survival.

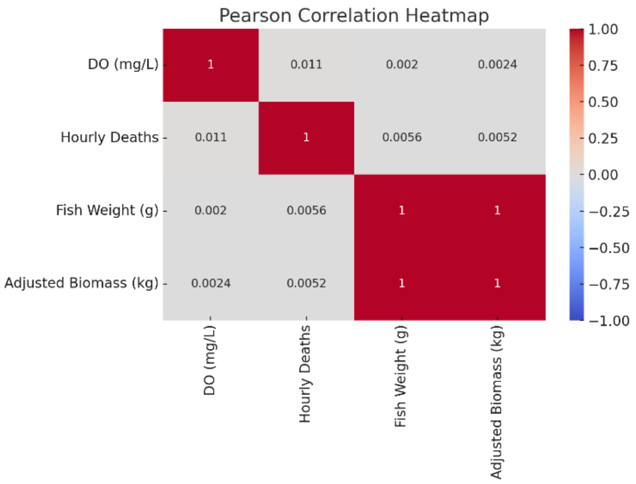

Figure 6. Heatmap for the pearson method

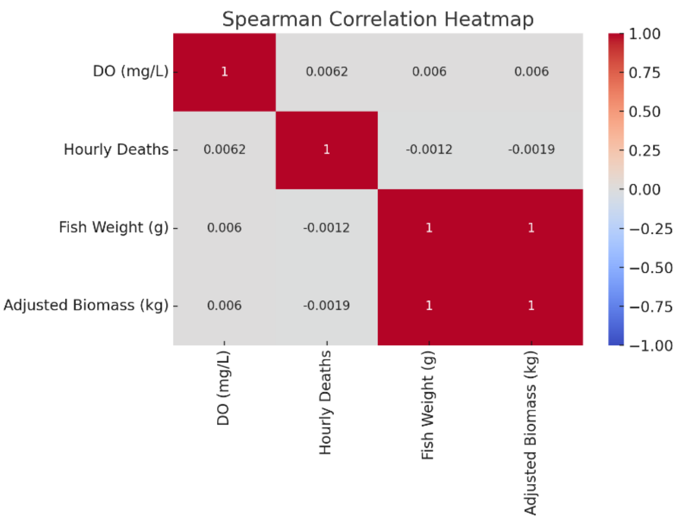

Figure 7. Heatmap for the pearson method

5. CONCLUSION

This study demonstrated the practical value of data-driven analysis in aquaculture by evaluating six months of operational data from a Patin (Pangasius hypophthalmus) farming cycle. Through comprehensive statistical, event-based, and economic analyses, the results confirm that structured feeding strategies, stable environmental management, and routine monitoring can lead to biologically and economically successful production outcomes.

Growth analysis showed a steady increase in fish weight, with a final average of approximately 901 grams per fish and a cumulative biomass of 2,100 kg at harvest. Feed utilization was efficiently managed through a phase-based feeding schedule, resulting in a Feed Conversion Ratio (FCR) of 1.56—well within industry norms. The consistent feeding strategy, aligned with fish development stages, not only supported healthy growth but also contributed to a favorable profit margin.

Mortality remained distributed and moderate, with a final survival rate of 85%, and environmental conditions such as dissolved oxygen, pH, and temperature were maintained within optimal thresholds throughout the cycle. Correlation analyses using both Pearson and Spearman methods revealed no significant relationships between environmental parameters and mortality or growth—further validating the effectiveness of environmental control during the production period.

Economically, the operation achieved a Return on Investment (ROI) of 173.5%, driven largely by stable feed efficiency and market-aligned harvest timing. The integration of routine data analysis—specifically tracking feed, biomass, survival, and environmental metrics—enabled a holistic understanding of system performance and provided a foundation for future optimization and automation.

In conclusion, the findings emphasize that precision aquaculture supported by continuous monitoring and analytics can significantly improve both biological outcomes and farm profitability. Future work will focus on real-time monitoring systems and predictive modeling to support decision-making in dynamic farming environments.

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